DECISION-MAKING IN THE FUTURE ELECTRICITY GRID: HOME ENERGY MANAGEMENT, PRICING DESIGN, AND ARCHITECTURE DEVELOPMENT

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Choisir, c'était renoncer pour toujours, pour jamais, à tout le reste –et la quantité nombreuse de ce reste demeurait préférable à n'importe quelle unité.

—André Gide

Chacune de nos décisions est une pâque, c'est-à-dire une forme de mort et de résurrection.

—François Varillon

J'ai *choisi* selon ma conscience. J'ai accepté de tout perdre et j'ai tout perdu.

—Hélie de Saint Marc

To choose, was to give up forever any chance of the remainder, and the innumerable quantity of that remainder always seemed preferable to any single item whatever.

—André Gide

Every decision we make is a passover, that is, a form of death and resurrection.

—François Varillon

I *chose* according to my conscience. I accepted to lose everything and everything I lost.

—Hélie de Saint Marc

To those who

have come before me

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Ad majorem Dei gloriam !

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SUMMARY

As the number of autonomous decision-making entities in the electricity grid increases, it is necessary to develop (1) new decision-making capabilities embedded within the grid's control and management, and (2) new grid architecture models ensuring that both individual and system objectives are met. This work develops (1) new decision-making mechanisms enabling residential energy users and electricity providers to interact through the use of dynamic price signals, and (2) policy recommendations to facilitate the emergence of shared architecture models describing the future state of the electricity grid. In the first part, two optimization models that capture the emerging flexible consumption, storage, and generation capabilities of residential end-users are formulated. An economic dispatch model that explicitly accounts for end-users' internal dynamics is proposed. A non-iterative pricing algorithm using convex and inverse linear programming is developed to induce autonomous residential end-users to behave cooperatively and minimize the provider's generation costs. In the second part, several factors that make the development of grid architecture models necessary from a public policy standpoint are identified and discussed. The grid architecture problem is rigorously framed as both a market failure legitimizing government intervention, and a meta-problem requiring the development of non-conventional methods of solution. A policy approach drawing on the theoretical concepts of broker, boundary object and boundary organization is proposed.

CHAPTER I

INTRODUCTION

Our energy system is undergoing fundamental changes to support the development of a sustainable society. In particular, significant investments are being made to transform electrical grids into 'smart grids' in an effort to address three inter-related challenges: energy security, economic growth and environmental protection. Contrary to the traditional grid components, all the decision-making agents present in emerging grids, either automated or human, will make decisions to achieve their individual objectives while contributing to the overall objectives of the grid. Thus, the secure evolution of the grid and its ability to realize its objectives depend on:

1. The development of *decision-making capabilities* embedded within the grid's control and management;

2. The development of a *shared, system-level vision* for the future state of the grid; this vision should engage the various decision-making entities involved, integrate their respective efforts, and eventually ensure that both *individual* and *system* objectives are met.

In this context, the objectives of the present research were twofold:

1. to develop specific decision-making mechanisms enabling residential energy users and electricity providers to interact through the use of electricity price signals;

2. to develop policy recommendations to facilitate the emergence of shared architecture models describing the future state of the electricity grid.

In this introductory chapter, we briefly present a generic framework encompassing the current and future decision-making entities across the grid at multiple spatial and temporal scales. The goal is to relate the various aspects of our work to this framework. We then provide an overview of the contributions of the present research to both the technical and policy fields.

The concept of *energy prosumer* allows us to formally represent both current *and* future decision-making entities across the grid. We define energy prosumers as cyber-physical entities that can consume, produce, store and/or transport electricity. Prosumers have their own objectives associated with the control and utilization of electricity. These objectives are aligned with the goals and preferences of the prosumer owners –individuals or organizations. Prosumers can also exchange energy services externally with other prosumers. Any decision-making component in today's electricity grid can be modeled as a prosumer. A home, a building, and a microgrid are each prosumers. A utility grid, an electric vehicle, and even individual appliances such as a laptop computer can also be represented as prosumers. The prosumer abstraction is also adapted to the future evolutions of the grid where each component is likely to gain access to additional energy functions.

The concept of *prosumer*, the *objective functions* set at the prosumer and system levels, and the concepts of *rules* and *mechanisms* from hierarchy theory [4] can all be used to characterize the grid and its constitutive entities from a decision-making standpoint (Figure 1.1).

At the *system level*, a community of decision makers consisting of prosumer owners, experts and elected officials set objectives for the entire grid. These objectives are multidimensional, and sometime contradictory; they vary over time as the various actors gain a shared understanding of (a) what the future grid should look like, and (b) how their environment is changing. Decision-makers at the system level also set *rules* that constrain both the way prosumers buy and sell energy services, and the

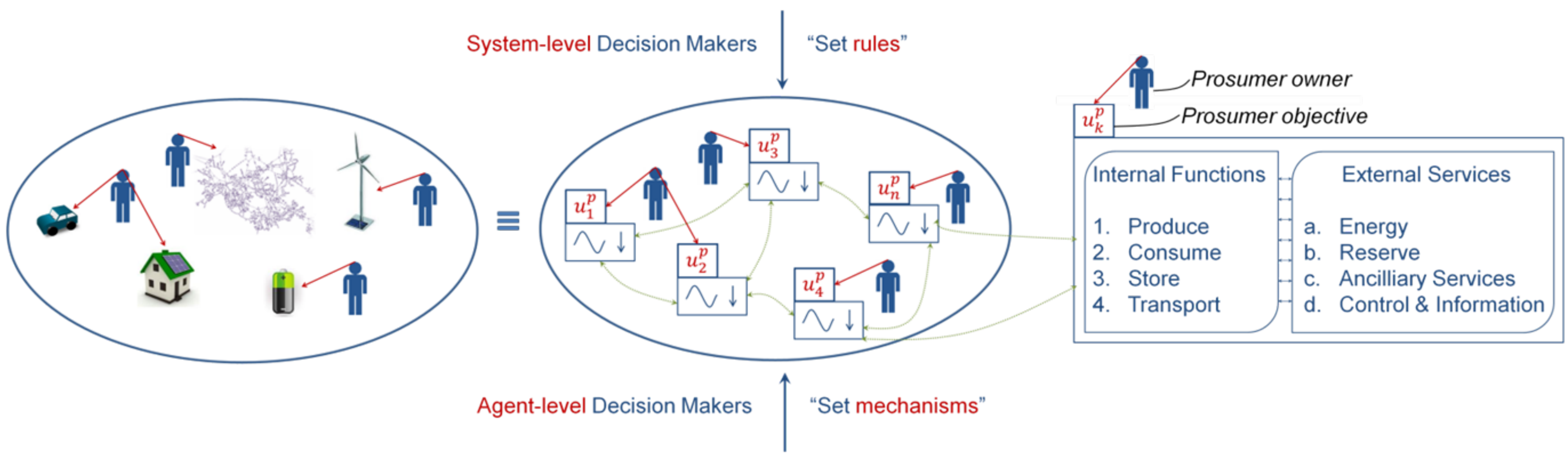


Figure 1.1: Prosumer-based representation of the electricity grid

way their internal functions are implemented. At the *prosumer level*, prosumer owners have their own goals and preferences associated with the control and utilization of electricity. Their objectives are based on a complex set of values (including economic, reliability, or sustainability aspects), and their objective functions also vary over time as they adapt to a changing environment. Prosumer owners set *mechanisms* to pursue their objectives within the rules set at the system level.

The present research relates to the generic framework summarized in Figure 1.1 as follows:

- The first two chapters focus on specific decision-making *mechanisms* enabling residential energy prosumers and electricity providers (which can be seen as prosumers of larger size) to interact through the use of electricity price signals: Chapter 2 presents an energy scheduling algorithm for residential prosumers based on mixed-integer linear programming. The goal of Chapter 2 is to illustrate the need for Home Energy Management Systems (HEMS) in the future electricity grid. Chapter 3 develops an electricity pricing scheme that induces autonomous residential prosumers to behave cooperatively and minimize the provider's generation costs. This pricing mechanism is to be used by electricity providers.

- Chapter 4 focuses on the process of elaborating *rules* for the future grid: policy recommendations are developed to facilitate the emergence of shared architecture models for the future grid.

The three chapters explore decision-making in the future electricity grid from different perspectives and are largely independent of one another. In Chapter 2, the decisions considered (namely: selecting an optimal energy usage strategy in response to dynamic prices) are made at the local level. These decisions impact primarily the residential prosumer himself, and secondarily the rest of the system. In Chapter

3, the decisions considered (namely: selecting the best pricing strategy) are made at the local level (the electricity provider makes the decision). These decisions aim to have a positive impact on some system-level objectives; they also have secondary effects on the prosumers. Finally, the decisions considered in Chapter 4 (namely: the development and selection of architecture models for the future grid) are made at the system level. These decisions aim to positively impact some system-level objectives. Figure 1.2 maps the loci and impact levels for the decisions considered in each of the three chapters.

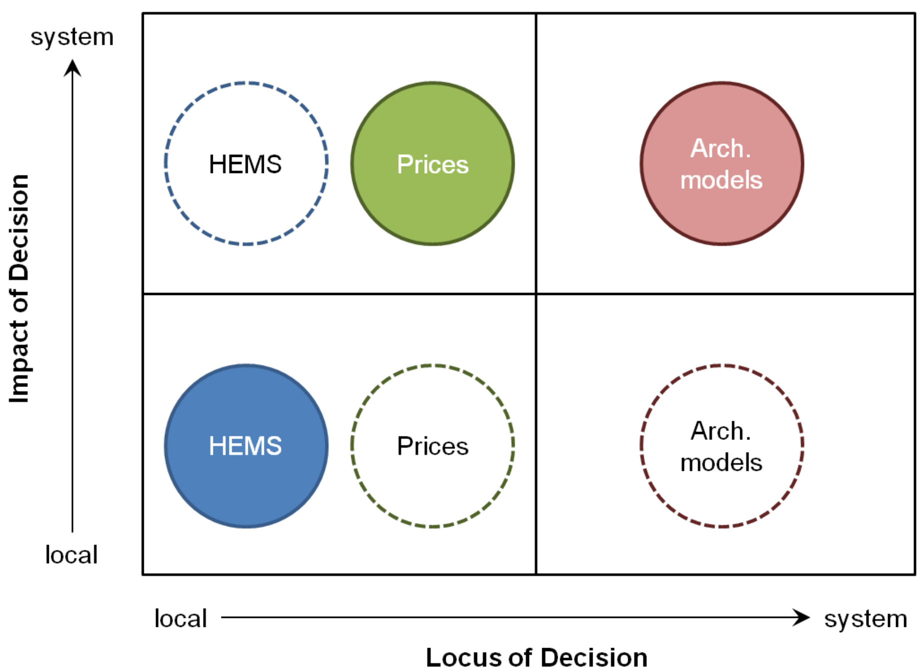


Figure 1.2: Loci and impact levels for the various types of decisions considered in the present work. *HEMS* refers to Chapter 2, *Prices* refers to Chapter 3, *Arch. models* refers to Chapter 4.

The technical contributions of the present research are as follows:

Contribution 1: We propose two optimization models that capture the emerging flexible consumption, storage, and generation capabilities of residential end-users as well as the ability to buy from *and* sell electricity to the provider. Existing models are usually limited to flexible consumption and do not account for bidirectional power flows.

Contribution 2: For any given end-user, we provide a sufficient constraint that allows us to model an arbitrary number of flexible loads with only one decision variable per time period. Existing models require one variable per time period *per flexible load*.

Contribution 3: We propose an economic dispatch model that explicitly accounts for end-users' internal dynamics. Existing models treat residential demand as an exogenous input. We propose to solve this enhanced economic dispatch in a distributed way using multi-level primal decomposition to reduce the size of the problem, and increase end-user privacy protection. To this end, we aggregate and disaggregate consumption, storage and generation capabilities across clusters of residential end-users.

Contribution 4: We propose a non-iterative pricing algorithm using convex programming and inverse linear programming. Different from existing non-iterative algorithms, our approach does not use backward induction and does not require closed-form expressions. To the best of our knowledge, this work is the first practical application of inverse linear programming.

Contribution 5: We ensure fairness by billing each end-user according to his contribution towards minimizing the provider's generation costs. Existing studies aim to select a pricing scheme that achieves optimality, but do not address the issue of fairness.

Contribution 6: We present extensive results obtained for two real-data test cases that demonstrate the proposed approach. Most existing studies present simulation results for test cases using synthetic data for the end-users.

The policy contributions of the present research are as follows:

Contribution 7: We identify and discuss three factors that make the development of architecture models necessary from a public policy standpoint: (1) the increasing collaborative nature of the grid, (2) the blurring of boundaries between the various disciplines concerned with the grid, and (3) the blurring of functions performed by some of the grid components.

Contribution 8: We rigorously frame the grid architecture problem as both a market failure legitimizing government intervention, and a metaproblem requiring the development of non-conventional methods of solution. We conceptualize the substantive problem as distances –spatial, temporal, conceptual and cultural– that prevent the various communities-of-practice involved to effectively cooperate.

Contribution 9: We propose a scalable policy approach to reduce these distances drawing on the concepts of broker, boundary object and boundary organization. An experiment of the proposed approach at the research group level is discussed and policy recommendations are provided to scale up the approach to the national level.

CHAPTER II

A MODEL FOR RESIDENTIAL ELECTRICITY OPTIMIZATION IN DYNAMIC PRICING ENVIRONMENTS

2.1 Introduction

Major forces are creating a new paradigm on residential electricity markets as energy optimization becomes an increasingly important challenge in our society[1]. New technologies are being deployed including advanced meters [29], controllable appliances [158], distributed generation [9], energy storage systems (PHEV batteries [128], stand-alone storage systems [5], [16]), and communications capabilities [98]. New legislations are being proposed to allow electricity consumers –and any third parties they designate– to access their electricity usage and pricing information [151], [14]. Finally, new dynamic pricing policies are likely to be implemented at the retail level over the next years [40, 41, 64, 149].

These multiple developments will contribute to enabling increased customer participation, one of the major objectives of the future grid [152]. Demand response actions in particular, could represent up to 45% of the expected smart grid benefits in the U.S. over the next decade [97]. Increased customers participation within the grid is a sign that the consumer-provider relation is changing, and could prefigure larger systemic changes across the electricity industry in the long term [55].

However, some of these changes have already caused backlash from customers, forcing for instance some energy providers to offer smart meter opt-out programs

[1]The work presented in this chapter was published in IEEE Transactions on Smart Grid, see [70]

[118]. Such conflicts between consumer empowerment and technology deployment –with groups of residential consumers choosing not to participate– could negatively affect the effectiveness of an integrated smart grid.

Stakeholders concerns regarding the ongoing changes include higher electricity bills [75], cyber-security, and privacy issues [120, 96, 102]. With new technologies deployed and new pricing policies implemented, the number of options offered to residential customers in terms of choices increases drastically. This also increases the number of decision parameters and makes home energy management too complex for the common user to solve manually. Additionally, while customers value usage or pricing information, they also want to be hands-off: the per capita time spent consuming information in the U.S. has risen nearly 60% from 1980 levels [8]. Increased complexity and information saturation eventually result in highly suboptimal energy utilization with customers not scheduling demand optimally, possibly leading to electricity bills higher than before.

Additional concerns from electricity providers and policy makers include the depth of impact that generalized dynamic pricing policies could have on consumption levels, the actual consumers ability to respond to price signals, and the practical implementation of these pricing policies. The systemic consequences and their impact on the stakeholders involved also need to be further analyzed and understood in order to take appropriate policy measures.

To address these concerns, advanced modeling of residential electricity consumers in a dynamic pricing environment is required. This chapter proposes an example of such modeling framework based on mixed-integer linear programming (MILP), with a robust optimization approach which minimizes the impact of stochastic input on the objective function while preserving acceptable running times. From an industry or policy perspective, this framework can be used to simulate and analyze the impact of the various ongoing changes on residential electricity markets—and in particular the use of dynamic pricing as a tool for effective demand side management [48]. From a consumer's perspective, this framework can be used to implement a home energy controller and minimize energy costs—a perspective developed in detail in this chapter.

In the recent literature [103, 104, 56, 28], it has been recognized that the scheduling problem that consists of coordinating and optimizing the operation of various energy sources and loads—in order to minimize the energy costs—can be formulated as a linear programming problem. Our modeling framework however differs from the recent literature in several ways. It covers the electricity consumption and generation functions, but also electricity storage, and the impact of these capabilities on the peak-toaverage ratio (PAR) is analyzed. It integrates loads with both continuous and discrete consumption levels, while the hourly-based consumption scheduled for each appliance is usually modeled as a continuous variable [103, 56, 28]. For this purpose, our MILP-based framework explicitly extends the formulation proposed in [103]. In [56], discrete variables are introduced, but with a coarser system granularity, which does not scale down to the appliance level. Finally, our framework introduces multiple time scales adapted to different types of devices. The work presented in this chapter extends our earlier conference paper [69] in several directions: we propose a full description of our modeling framework, and extend our previous discussion to scenarios involving multiple electricity providers; stochastic inputs are treated with a robust optimization approach to decrease uncertainty at an acceptable computational cost; complex pricing mechanisms are considered; finally, performance of the proposed solution is assessed against a reference case.

The rest of this chapter is organized as follows. Section 2.2 defines the electrical system considered. Section 2.3 discusses modeling aspects. Section 2.4 describes the optimization constraints considered. Section 2.5 formulates the optimization problem and proposes a solution method. Section 2.6 defines a reference case for comparisons and Section 2.7 evaluates the performance of the proposed method. Section 2.8 concludes this chapter.

2.2 System definition

An electrical home can be defined as a small-scale energy system operating at the home level. In this chapter, the electrical system considered in order to mathematically formulate the optimization problem consists of the following components: a set of solar photovoltaic modules, a small wind turbine, a standalone genset, an energy storage system, an electric vehicle, and a set of controllable and non-controllable appliances. The system considered can easily be tailored to a specific home grid configuration by disabling some of the components mentioned above if needed.

The non-controllable appliances include all the domestic appliances the consumer wants to be able to turn on and off immediately, such as TV, microwave, lights, etc. These loads cannot be integrated into a fully automated optimization process. The controllable appliances include appliances such as a dishwasher, the defrost mode of a freezer, a Heating, Ventilation, and Air Conditioning (HVAC) system, or a water heater tank. The consumer is more flexible with these appliances as long as they fulfill their role. The controllable appliances divide up into interruptible appliances, such as HVAC systems, which may be interrupted immediately, and non-interruptible appliances, such as a dishwasher or a washing machine, which are not designed to allow unexpected interruptions when their cycle has started.

We assume that weather forecasts allow a day-ahead estimation of the expected values of local energy production, and that signals giving the electricity prices over a time horizon D are available. We assume the presence of a module able to forecast the expected values of the non-controllable appliances consumption based on the home grid history data.

Our objective is to optimize the energy use –minimize the energy costs– of the

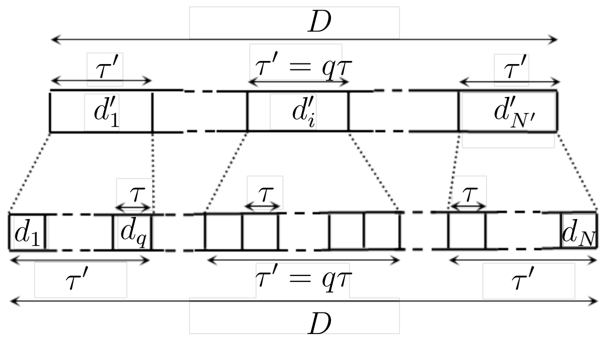


Figure 2.1: Relation between the temporal subdivisions d and d'

electrical system considered over a given time horizon D.

2.3 Time and component modeling

2.3.1 Time horizon subdivisions

Scheduling of such a variety of electric loads with behavior relevant at different time scales requires handling temporal subdivisions. The time horizon D is divided into N' adjacent time intervals d'_i of same length τ'. Define $d' = \{d'_1, d'_2, ..., d'_i, ..., d'_{N'}\}$ a subdivision of D. Over a given interval d'_i the amount of power consumed or produced by each home grid component is assumed to be constant. Also define a second subdivision by dividing each initial interval d'_i into a new set q of adjacent time intervals d_j of equal length τ (Fig. 2.1). The initial subdivision d' is well adapted to the non-interruptible loads, while the new subdivision d, more precise, is particularly adapted to the HVAC system for instance which is likely to have a smaller characteristic time.

2.3.2 Storage system

The amount of energy $E > 0$ stored in the energy storage system (ESS) is one of the state variables allowing for computing the evolution of the electrical system considered over time. In the following formulation, E does not include any minimal amount of energy E^{min} which would have to remain in the ESS at all times for technical reasons. We define $R^c > 0$ as the maximal charging rate, and $R^d > 0$ as the maximal discharging rate.

The age and past history of the ESS, the number and frequency of charging and discharging cycles, the depth-of-discharge, as well as other factors may degrade performance over time [37]. In the following, we assume that E^{max}, R^c, R^d remain constant over time horizon D.

2.3.3 Non-interruptible appliances

Non-interruptible appliances are different because of their discrete behavior: the appliance cycle is approached by a block of k_L adjacent time intervals of length $k_L\tau', k_L \in \{0, 1, ..., N'\}$. There are $S_L = N' - k_L + 1$ positions possible to schedule the load L over D. Each position j is assigned a binary number $\delta_j^L \in \{0, 1\}$ with $\delta_j^L = 1$ if the load L is scheduled in the position j, and $\delta_j^L = 0$ otherwise. We call ℓ the number of non-interruptible appliances.

2.3.4 Thermodynamic system

The thermodynamic system that models the house exchanges heat with two other systems, the HVAC and the outside. In the following derivation, as an approximation, the house is modeled as one room. This modeling could be extended using the same formulation, to account for internal heat transfers.

The classic thermodynamics equations apply [45]:

$$\begin{aligned}
\forall t \in D, \quad & \frac{dT^r(t)}{dt} && = \frac{1}{M_{air} \cdot c}\left\{\left(\frac{dQ^r(t)}{dt}\right)_{HVAC} - \left(\frac{dQ^r(t)}{dt}\right)_{losses}\right\} && (1)\\
\forall t \in D, \quad & \left(\frac{dQ^r(t)}{dt}\right)_{HVAC} && = \dot{M} \cdot c && (2)\\
\forall t \in D, \quad & \left(\frac{dQ^r(t)}{dt}\right)_{losses} && = \frac{T^r(t) - T^{out}(t)}{R_{eq}} && (3)
\end{aligned}$$

with T^r the room temperature, T^{out} the outside temperature, T^h the supply air temperature, M_{air} the mass of air inside the house, c the specific heat capacity of air at constant pressure, $\dot{M}$ the air flow rate through the HVAC, R_{eq} the equivalent thermal resistance of the house, $(dQ/dt)_{losses}$ the quantity of heat exchanged between the room and the outside, $(dQ/dt)_{HVAC}$ the quantity of heat exchanged between the room and the HVAC. R_{eq} can be estimated at first based on geometrical considerations, and then be refined over time based on both room and outside temperatures history.

For the time subdivision d, define $T_i^{r,0}$ the temperature of the room at the beginning of the time interval d_i and T_i^r the function defined on d_i such that T_i^r and T^r are identically equal on d_i. The initial condition is given by $T^{init} = T_1^{r,0}$.

Assume that N is large enough so that $\tau \ll \tau_{T^{out}}$, with $\tau_{T^{out}}$ the characteristic time of T^{out}. Then we can assume that T^{out} is constant on and equal to T_i^{out}. We also assume that the quantity of heat $(dQ/dt)_{HVAC}$ is maintained constant on d_i and equal to P_i^h. $(dQ/dt)_{HVAC}$ is controlled over time through the parameters T^h and $\dot{M}$ to meet the user comfort preferences. In winter time, heat is transferred to the room and $P_i^h > 0$. In summer time the heat flow is reversed and $P_i^h < 0$.

From (1) and (3) we have:

$$\forall t \in d_i, \quad \frac{dT_i^r(t)}{dt} + \frac{T_i^r(t)}{M_{air} \cdot c \cdot R_{eq}} = \frac{P_i^h}{M_{air} \cdot c} + \frac{T_i^{out}}{M_{air} \cdot c \cdot R_{eq}} \tag{4}$$

Solving the differential equation for T_i^r with the origin of time being taken at the beginning of d_i :

$$\forall t \in d_i, \quad T_i^r(t) = (T_i^{r,0} - R_{eq}P_i^h - T_i^{out})exp(\frac{-t}{M_{air} \cdot c \cdot R_{eq}}) + R_{eq}P_i^h + T_i^{out} \tag{5}$$

2.3.5 Recursive relation giving ESS charging status

Define for each interval d_i the following parameters:

E_i^0 : the amount of energy stored at the beginning of the interval;

$P_i^{(g)}$: the power exchanged between the home grid and the distribution grid with $P_i^{(g)} > 0$ when power is transferred from the distribution grid to the home grid;

$P_i^{(gs)}$: the power generated by the stand-alone genset;

$P_i^{(s)}$: the power generated by the photovoltaic modules;

$P_i^{(w)}$: the power generated by the small wind turbine;

$P_i^{(cl)}$: the power consumed by the controllable loads (interruptible and non-interruptible);

$P_i^{(ncl)}$: the power consumed by the non-controllable loads.

The recursive relation between E_{i+1}^0 and E_i^0 is:

$$\begin{aligned} E_1^0 &= E^{init} \\ E_{i+1}^0 &= E_i^0 + (P_i^{(g)} + P_i^{(bt)} + P_i^{(s)} + P_i^{(w)} - P_i^{(cl)} - P_i^{(ncl)}) \cdot \tau \end{aligned} \tag{6}$$

2.4 Optimization constraints

The electrical system considered operates over time under several constraints related to physical, modeling, comfort and electricity markets considerations.

2.4.1 Physical constraints

The storage system is constrained by its maximum capacity and its charging and discharging rates:

$$\forall t \in D, \quad 0 \leq E(t) \leq E^{max} \tag{7}$$

$$\forall t_1, t_2 \in D, \quad -R^d \leq E(t_2) - E(t_1) \leq R^c \tag{8}$$

For the time subdivision d, the corresponding constraints (9), (10), (11), and (12) are derived from (6), (7) and (8).

$\forall n \in \{1, 2, ..., N\}$,

$$-\sum_{i=1}^{n}(P_i^{(g)} + P_i^{(bt)} - P_i^{(cl)})\tau \leq E^{init} + \sum_{i=1}^{n}(P_i^{(s)} + P_i^{(w)}) \tag{9}$$

$$\sum_{i=1}^{n}(P_i^{(g)} + P_i^{(bt)} - P_i^{(cl)})\tau \leq E^{max} - E^{init} - \sum_{i=1}^{n}(P_i^{(s)} + P_i^{(w)}) + \sum_{i=1}^{n} P_i^{(ncl)}\tau \tag{10}$$

$$(P_i^{(g)} + P_i^{(bt)} - P_i^{(cl)})\tau \leq R^c - (P_i^{(s)} + P_i^{(w)})\tau + P_i^{(ncl)}\tau \tag{11}$$

$$-(P_i^{(g)} + P_i^{(bt)} - P_i^{(cl)})\tau \leq R^d + (P_i^{(s)} + P_i^{(w)})\tau - P_i^{(ncl)}\tau \tag{12}$$

The HVAC system is constrained by its thermal capacity. Assume that the maximum quantity of heat that can be either transferred to or removed from the room is $P^{h,max} > 0$ in absolute value. Then,

$$\forall i \in \{1, 2, ..., N\}, |P_i^h| < P^{h,max} \tag{13}$$

Additionally, T^r is a continuous function, therefore T_i^r is continuous and the continuity at the boundary between d_i and d_{i+1} gives:

$$T_i^r(\tau) = T_{i+1}^{r,0} \tag{14}$$

Expressing $T_i^r(\tau)$ with (5), we obtain the following condition:

$$T_i^{r,0} K_\tau - T_{i+1}^{r,0} + R_{eq}(1 - K_\tau) P_i^h = (K_\tau - 1) T_i^{out} \tag{15}$$

with:

$$K_\tau \triangleq exp(\frac{-\tau}{M_{air} \cdot c \cdot R_{eq}}) \tag{16}$$

The stand-alone genset is limited by its generation capacity $P^{gs,max}$:

$$\forall i \in \{1, 2, ..., N\}, P_i^{(gs)} < P^{gs,max} \tag{17}$$

Finally, the amount of power that can be transferred from the distribution grid to the home grid is limited by the line capacity $P^{g,max} > 0$ at the point of common coupling (PCC):

$$\forall i \in \{1, 2, ..., N\}, |P_i^{(g)}| < P^{g,max} \tag{18}$$

2.4.2 Modeling constraints

The number of times each non-interruptible appliance is to be scheduled over D is defined by the residential consumer. If load L is to be scheduled γ^L times over D, we must have:

$$\sum_{j=1}^{S_L} \delta_j^L = \gamma^L \tag{19}$$

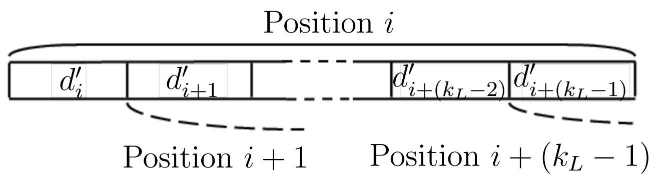


Figure 2.2: Non-overlapping conditions for each appliance

In addition, the same appliance cannot be scheduled more than once per time interval, which means that two cycles cannot overlap (Fig. 2.2). Therefore we must have:

$$\left.\begin{array}{l}
\forall i \in \{1, 2, ..., S_L - (k_L - 1)\}, \\
\qquad (k_L - 1) \text{ conditions} \begin{cases} \delta_i^L + \delta_{i+1}^L \leq 1 \\ \delta_i^L + \delta_{i+2}^L \leq 1 \\ \dots\dots\dots\dots \\ \delta_i^L + \delta_{i+k_L-1}^L \leq 1 \end{cases} \\
\text{If } i = S_L - (k_L - 2), \\
\qquad (k_L - 2) \text{ conditions} \begin{cases} \delta_i^L + \delta_{i+1}^L \leq 1 \\ \delta_i^L + \delta_{i+2}^L \leq 1 \\ \dots\dots\dots\dots \\ \delta_i^L + \delta_{i+k_L-2}^L \leq 1 \end{cases} \\
\text{If } i = S_L - (k_L - 3), \\
\qquad (k_L - 3) \text{ conditions} \begin{cases} \delta_i^L + \delta_{i+1}^L \leq 1 \\ \delta_i^L + \delta_{i+2}^L \leq 1 \\ \dots\dots\dots\dots \\ \delta_i^L + \delta_{i+k_L-3}^L \leq 1 \end{cases} \\
\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \\
\text{If } i = S_L - (k_L - (k_L - 1)) = S_L - 1, \\
\qquad 1 \text{ condition} \quad \{ \quad \delta_i^L + \delta_{i+(k_L-(k_L+1))} \leq 1
\end{array}\right\} \quad (20)$$

2.4.3 Comfort preference constraints

The consumer's comfort preferences on T^r over D are transposed into two limit functions $T^{r,min}$ and $T^{r,max}$ defined on D and discretized according to the subdivision d.

$$\forall i \in \{1, 2, ..., N\}, \quad T_i^{r,min} \leq T_i^{r,0} \leq T_i^{r,max} \tag{21}$$

Additionally, based on the consumer's comfort preferences regarding each controllable, non-interruptible load L, a set of positions Ω^L over which load L cannot be functioning is defined:

$$\forall j \in \Omega^L, \quad \delta_j^L = 0 \tag{22}$$

2.4.4 Electricity market constraints

In the following we assume that residential consumers can engage in energy transactions with μ different electricity providers, $\mu > 1$. For each interval d_i, define as $P_i^{(g,k,+)} > 0$ the power delivered by provider k to the residential consumer at the point of common coupling (PCC). Similarly, define as $P_i^{(g,k,-)} > 0$ the power delivered by the residential consumer to provider k at the PCC. Define as $\mathcal{P}^{k,+}$ and $\mathcal{P}^{k,-}$ the price vectors at which provider k offers to sell and buy electricity over D, respectively. In the following, we assume that $\mathcal{P}^{k,+}$ and $\mathcal{P}^{k,-}$ come with a cap $P^{k,+,max}$ and $P^{k,-,max}$, respectively. These correspond to the maximum amount of power that provider k is willing to buy or sell at the proposed prices. These two caps reflect the limited transmission capabilities of the distribution grid as well as other network contingencies that provider k must account for when formulating his offer. We assume that the same caps apply to every interval d_i. Therefore, we must have:

$$\forall i \in \{1, 2, ..., N\}, \qquad P_i^{(g,k,+)} < P^{g,+,max} \tag{23}$$

$$\forall i \in \{1, 2, ..., N\}, \qquad P_i^{(g,k,-)} < P^{g,-,max} \tag{24}$$

Provider k may transmit several price vectors corresponding to several options regarding the cap values, the variations in the cap values being reflected in the prices. Additionally, multiple price signals may also be used to differentiate offers based on emission levels. In this last case, a subset of price vectors is defined according to the consumer's environmental preferences. Only those price vectors are later considered when solving the optimization problem.

2.5 Problem formulation and optimization

2.5.1 Problem formulation and method of solution

Based on the set of constraints presented in Section 2.4, we formulate the power scheduling problem over as a mixedinteger linear programming (MILP) problem [119] which can be efficiently solved using GUROBI.

The $(2\mu+4)N+\sum_{i=1}^{\ell} S_{L_i}+1$ unknowns consists of the amounts of power bought from and sold to each provider, the power generated by the genset over time, the binary numbers representing the scheduling positions of each appliance, the room temperature at the beginning of each interval d_i, and the power consumed by the HVAC in the cooling and heating modes. The objective function $\mathcal{C}$ is defined as the total electricity cost and is to be minimized over the time period considered.

In the following, we assume that each provider provides a quadruplet ($\mathcal{P}^{k,+}$, $P^{k,+,max}$, $\mathcal{P}^{k,-}$, $P^{k,-,max}$) with $P^{k,+,max} = P^{k,-,max} = P^{g,max}$. Additionally, we also assume that each provider offers to scale $\mathcal{P}^{k,+}$ logarithmically if the consumer agrees to reduce the power cap. For $\kappa \in [0,1]$, the scaling factor corresponding to a power cap $\kappa \cdot P^{k,+,max}$ is defined as $log(\kappa P^{k,+,max})/log(P^{k,+,max})$. This pricing mechanism reflects the willingness of each provider to encourage residential consumers to smooth their energy consumption as much as possible over time. This corresponds to a peak-to-average ratio (PAR) decreasing towards 1.

The MILP problem is solved for several values of κ using a divide and conquer algorithm in order to approach the power cap that minimizes $\mathcal{C}$. If $\mu > 1$, in order to

Algorithm 1: Decision making process on the residential consumer side under the proposed problem formulation

1: Solve MILP problem for initial caps $P^{1,+,max}, ..., P^{\mu,+,max}$ ($\kappa = 1$)
2: **while** $(BestCost - NewCost) < \varepsilon$
3: Set $BestCost \triangleq NewCost)$
4: Solve MILP problem for a different value of κ using divide and conquer algorithm
5: **end while**

simplify the search process, we approach the optimal cap by assuming that the same κ applies to all providers, i.e. the power caps are the same for all providers.

Algorithm 1 summarizes the proposed decision making process on the residential consumer side to determine the optimal energy consumption schedule over D.

2.5.2 Uncertainty on forecasted inputs

Errors on weather forecast and non-controllable consumption forecasts affect the final value of the objective function. Complex forecasting algorithms for wind, solar and non-controllable consumption are outside of the scope of this chapter. Therefore, we assume in the following that the forecast errors on the solar irradiance and non-controllable consumption follow normal distributions. The case below does not consider wind, but wind power could also be modeled, including complex error distributions [51]. As the industry moves towards better forecasting, the outcomes of the proposed optimization tool will be further enhanced.

We follow a robust optimization approach to decrease the uncertainty on forecasted inputs at an acceptable computational cost. For the solar irradiance forecast, we take the lower limit of the 95% confidence interval over D. Note that the standard error of the irradiance forecast can be modeled as a polynomial function of the clear sky index and the cosine of the solar zenith angle [90]. For the non-controllable consumption, we take the upper limit function of the 95% confidence interval. The performance of this robust approach is further discussed in Section VII.

Table 2.1: Values of physical constraints

Symbol	Quantity	Assumed value
$P^{g,max}$	Line capacity at PCC	20kW
E^{init}	Energy stored at t=0	0kWh
E^{max}	Maximum capacity, ESS	25kWh
R^c, R^d	Max. charging/discharging rates, ESS	6kW
$P^{h,max}$	Max. quantity of heat exchanged between room and HVAC	20kWe
$P^{gs,max}$	Max. power output, solar pamels	9kWp

2.5.3 Example

We simulate a summer time scenario involving $\mu = 3$ energy providers, with $\ell = 6$ interruptible loads. We set $D = 24h$, $\tau' = 5min$ and $\tau = 2.5min$. Detailed consumption profiles with a 1.5 min resolution are available for the washing machine, dryer, dishwasher and defrost cycle of the fridge. These profiles are re-sampled with a time step equal to τ. Average power consumptions are available for the water heater and the PHEV battery.

Additionally, this example includes an ESS and a solar panel. Table 2.1 shows the characteristic parameters assumed.

For the non-controllable consumption forecast, we assume the 95% confidence limits to be at 20% of the expected value. This assumption is further discussed in Section 2.7. The expected value and standard error functions of the solar irradiance are hourly predictions derived from actual data [90].

The price signals used for the example were taken from actual day-ahead price signals from PJM wholesale market scaled to reflect an average price of 12 /kWh.

We assume that the user has defined the following comfort preferences: room temperature to remain between $20°C$ and $25°C$ at all times; dishwasher, washing machine and dryer to run each once between 8:00am and 6:00pm; defrost cycle of the fridge to run once over the next 24 hours; water heater cycle to run twice over the next 24hours; PHEV battery to charge 8 times 15min between 24:00am and 24:00pm.

Algorithm 1 returns the optimal schedule corresponding to a minimized cost of 0.59, with $\kappa = 4.3\%$. The defrost mode starts at 10:50pm; the dishwasher starts at 9:10am; the washing machine starts at 10:20am; the dryer starts at 12:10pm; the water heater starts at 11:30 and 11:45pm; the PHEV battery charges continuously from 6:10am to 8:10am. Fig. 2.4 gives the optimal schedule of the HVAC; the room temperature remains within the comfort limits (Fig. 2.3). Fig. 2.5 gives the optimal schedule of the ESS. The ESS is empty at the end of D: this is consistent with the fact that the end-user wants to maximize his benefits over D.

The pricing mechanism is successful in encouraging the user to schedule its controllable loads as well as its ESS in such a way that the net power exchanged with each provider is mostly flat (Fig. 2.6).

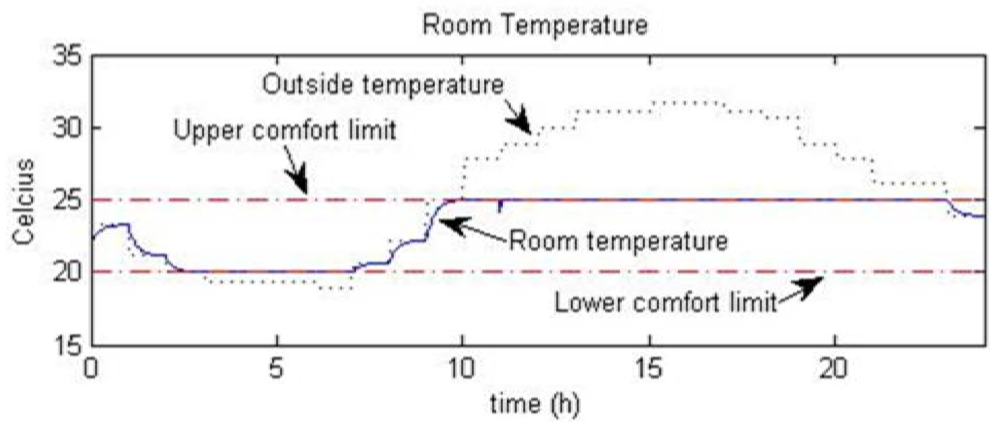


Figure 2.3: Evolution of room temperature over D

2.6 Definition of a reference case

In order to evaluate the performance of Algorithm 1, we define a reference case where residential users have limited decision making capabilities to optimize their energy usage.

Under the reference case, each controllable, non-interruptible appliance which is to run over D is started randomly within the user's comfort preferences defined by Ω^L.

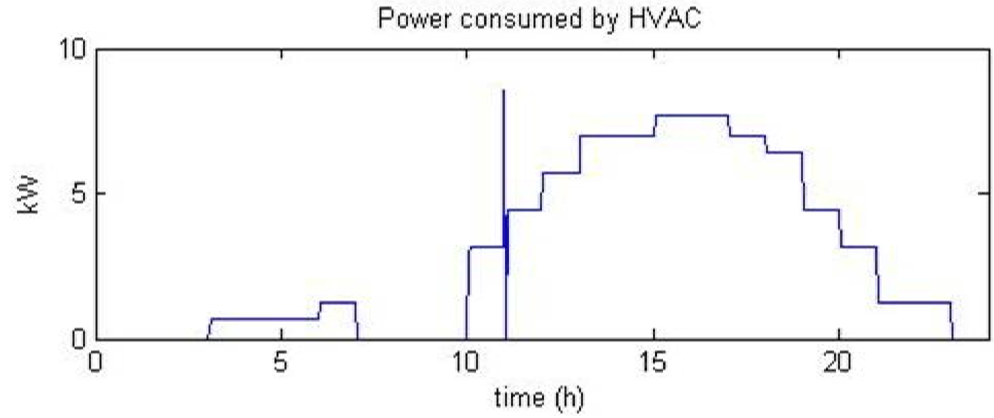


Figure 2.4: Optimal HVAC consumption schedule over D

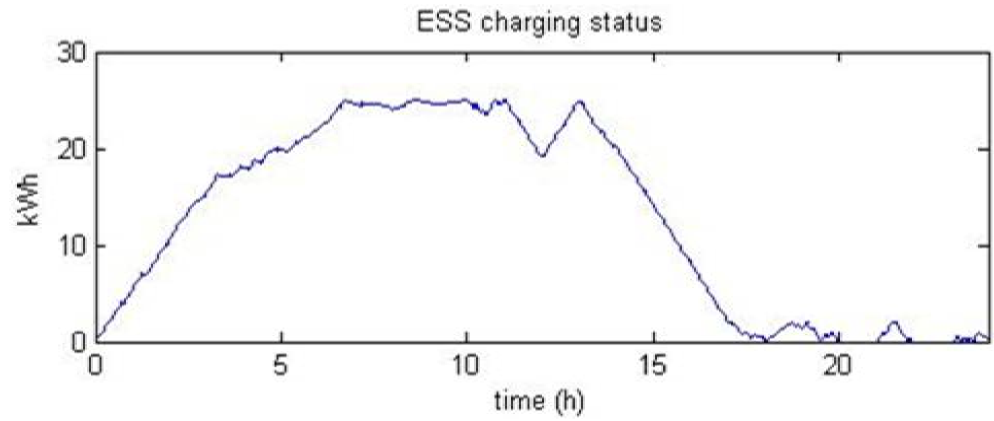


Figure 2.5: Optimal ESS charging status over D

The HVAC has a cooling mode and a heating mode. We assume that the quantity of heat exchanged with the room for each mode is fixed when the HVAC is on. At the beginning of each interval, if the room temperature is outside of the comfort preference constraints, the HVAC switches on to the corresponding mode.

If $\mu > 1$, we assume that for each interval d_i a very basic algorithm is able to select the providers offering to sell electricity at the lowest price, and to buy at the highest price.

If a ESS is present, when the lowest selling price is below (respectively: above) a given threshold, the ESS charges (respectively: discharges) at the highest rate possible enforcing the ESS physical constraints as well as the power transfer constraints at the

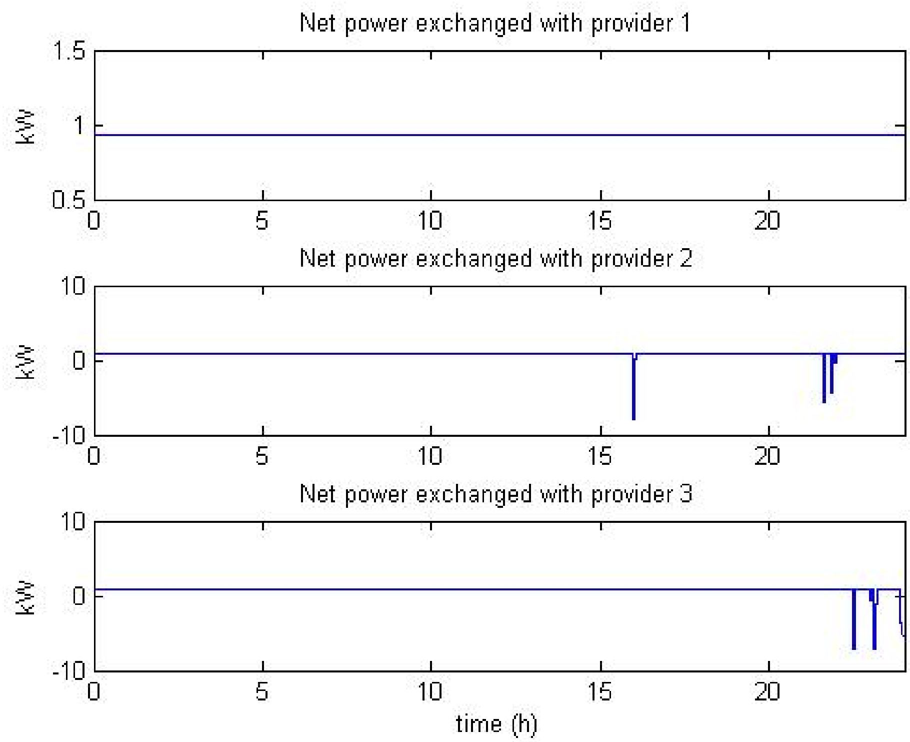


Figure 2.6: Power exchange with providers at PCC over D

PCC.

If a genset is present, whenever the net energy consumption of the house is positive, if running the genset is less expensive than the lowest selling price, the genset covers as much of the house power consumption as possible. If the genset has not reached its maximum capacity yet, if running the genset costs less than the highest buying price, the genset sells as much power as possible to the grid within power transfer constraints at the PCC.

Algorithm 2 summarizes the decision making process on the residential consumer side under the reference case.

2.7 Performance evaluation

In this section, we define several simulation scenarios, discuss simulation results, and assess the performance of our proposed algorithm.

Algorithm 2: Emulation of the decision making process on the residential consumer side under the reference case

```
schedule appliances randomly over D within comfort constraints
for i = 1..N
    if μ > 1
        select best buying and selling providers
    end if
    if T_i^{r,0} outside of comfort preference constraints
        start HVAC accordingly
    end if
    if best selling price < ESS price threshold
        charge at the highest rate prossible
    else
        discharge at the highest rate possible
    end if
    if power transferred from the grid to the house > 0
        if genset less expensive than providers
            start genset to cover as much of the house consumption as possible
        end if
        if best buying price > cost to run genset
            use genset to sell as much as possible to the grid
        end if
    end if
end for
```

2.7.1 Scenarios simulated

A simulation scenario is defined by a given home grid configuration, an algorithm (proposed or reference method), and a number of providers. When the reference method is used, results are averaged over a large number of simulations to account for the random distribution of appliances.

Under the reference case, the price signals considered can be either day-ahead prices (referred subsequently as the R-DA case) or real-time prices (R-RT case), depending on the existence of a real-time market at the retail level. In addition to the objective function $\mathcal{C}$, the peak-to-average ratio (PAR) is also computed for each scenario considered.

All the scenarios are computed for D=24 hours starting at midnight, with $\tau' = 5min$ and $\tau = 2.5min$. The characteristics of the home grid components and the comfort preferences are identical to those used in the example of Section 2.5. The price signals used are taken from actual price signals from PJM wholesale market and scaled.

When electricity price signals are flat, residential consumers have no incentive to shift their demand consumption overtime. However, for comparison purposes, we computed the flat price scenario for a home grid consisting of controllable and non-controllable loads only (and with $\mu = 1$). Under the reference case, $\mathcal{C}$ = \$12.38 with day-ahead prices, and $\mathcal{C}$ = \$14.75 with real-time prices, with $PAR = 4.20$ in both cases. Under the optimized case, $\mathcal{C}$ = \$12.16 with $PAR = 2.07$. The significant reduction in the PAR reflects the presence of consumption spikes under the reference case due to the dumb control strategy of the HVAC.

Tables 2.2 and 2.3 present simulation results for scenarios involving dynamic price signals. The technology capabilities are incrementally increased, starting with load scheduling only, and then adding successively the ESS, the ability to sell electricity at the PCC, and the ability to generate electricity (solar panels, and finally genset).

Table 2.2: Comparison between reference and proposed methods for $\mu = 1$

Technology	Rerefence case, real-time prices (R-RT case)		Rerefence case, day-ahead prices (R-DA case)		Proposed algorithm, robust approach	
	$\mathcal{C}$(\$)	PAR	$\mathcal{C}$(\$)	PAR	$\mathcal{C}$(\$)	PAR
Load scheduling	18.29	4.19	14.86	4.18	13.11	2.07
+ESS	16.67	3.75	13.61	4.17	10.39	1.18
+Ability to sell	16.79	3.49	13.28	3.78	10.18	1.00
+Solar panels	7.38	4.25	6.98	4.69	4.55	1.00
+Genset	5.02	4.54	6.82	5.18	4.40	1.00

Table 2.3: Comparison between reference and proposed methods for $\mu = 3$

Technology	Rerefence case, real-time prices (R-RT case)		Rerefence case, day-ahead prices (R-DA case)		Proposed algorithm, robust approach	
	$\mathcal{C}$(\$)	PAR	$\mathcal{C}$(\$)	PAR	$\mathcal{C}$(\$)	PAR
Load scheduling	14.35	4.18	14.17	4.18	12.78	1.55
+ESS	13.50	3.49	13.02	4.11	10.26	1.41
+Ability to sell	13.48	3.49	11.52	3.70	6.23	1.02
+Solar panels	4.39	4.29	6.43	4.66	0.59	1.01
+Genset	2.53	5.18	6.22	5.19	0.42	1.01

2.7.2 Computational performance

Simulations were run on an Intel Xeon 4-core processor at 2.53 GHz with 6 GB of memory. The average running time of the proposed algorithm for the scenarios presented in Tables 2.2 and 2.3 was 231.8 seconds, with a maximum at 414.9 seconds. From a practical implementation standpoint, the algorithm could be run either locally, assuming the presence of a good solver, or by third parties providing computational capabilities to the residential consumer. Access of energy usage information by third parties is explicitly considered in [151].

2.7.3 Economic gains of users

Tables 2.2 and 2.3 show that, for a given technology portfolio, the proposed algorithm always outperforms the reference case.

In the basic scenario with the user limited to scheduling controllable loads, the economic gain varies from 9.8% ($\mu = 3$, against R-DA case) to 28.3% ($\mu = 1$, against R-RT case). In presence of the ESS, the proposed method improves the objective function by 21.2% to 37.7%. If the consumer also has the ability to sell power at the PCC, the proposed method outperforms the reference case by 23.3% to 53.8%. Finally, if the solar panel is also connected to the home grid, the proposed method outperforms the reference case by 34.9% to 86.6%.

Note that the R-RT and R-DA scenarios limited to load scheduling capabilities always lead to higher bills than the corresponding flat price scenario previously discussed. This illustrates suboptimal energy utilization when residential customers are to deal with dynamic pricing environments not equipped with the proper decision tools.

2.7.4 Comparison with perfect forecasts

The proposed method reduces uncertainty by considering conservative non-controllable consumption and power generation forecasts (robust approach). If the user follows

Table 2.4: Error introduced by robust approach for $\mu = 1$

Technology	Robust approach $\mathcal{C}$ (\$)	Perfect forecast $\mathcal{C}$ (\$)	Absolute error (\$)	Percent error
Load scheduling	13.11	12.69	0.42	3.32
+ESS	10.39	9.93	0.45	4.56
+Ability to sell	10.18	9.69	0.48	4.99
+Solar panels	4.55	2.55	2.00	78.47
+Genset	4.40	2.37	2.03	116.75

the optimal schedule returned by the proposed algorithm, there is a high probability that the actual value of the cost function will be equal or less than the value returned by the algorithm. Because the non-controllable loads will probably consume less than the upper limit of the 95% confidence interval, and the solar panels will probably produce more than the lower limit, the user will probably end up with more energy than needed. This energy can be either stored or sold in the electricity market.

Table 2.4 compares (for $\mu = 1$) our robust approach with the case where the perfect forecasts would be known ahead of time.

The objective function returned is always over-estimated compared to the perfect case, especially when solar panels start being considered. Still, the proposed approach is always outperforming the reference case at approaching the perfect forecast (Table 2.2).

2.7.5 Sensitivity analysis on the confidence intervals of the non- controllable consumption forecast

We previously assumed the 95% confidence intervals of the non-controllable consumption forecast to be at +/- 20% of the expected value. Table 2.5 shows the impact on $\mathcal{C}$ of wider confidence intervals. The maximum variation observed in Table 2.5 is +\$2.01, but the variation remains below +\$0.95 for 95% confidence limits at up to +/- 60% of the expected value.

Table 2.5: Impact on the objective function of wider confidence intervals for the non-controllable consumption forecast ($\mu = 1$)

Technology	$\mathcal{C}$ (\$) for 95% confidence limits at +/-X% of the expected value				
	$X = 20$ (reference)	$X = 40$	$X = 60$	$X = 80$	$X = 100$
Load scheduling	13.11	13.57	14.00	14.41	14.86
+ESS	10.39	10.80	11.24	11.62	12.01
+Ability to sell	10.18	10.64	11.13	11.27	11.72
+Solar panels	4.55	5.03	5.48	6.04	6.56
+Genset	4.40	4.86	5.30	5.74	6.19

2.7.6 Performance gains of providers

In the reference case, we observe that PARs decrease when the ESS is considered, but re-increases when the distributed generation is put online. This reflects the fact that the average power transferred from the grid to the house decreases because of the local generation. The proposed algorithm significantly reduces the PAR compared to the R-RT and R-DA cases (up to 80%). This reduction can be explained by the better control scheme of the HVAC system, and by the pricing mechanism which encourages the user to smooth the quantities of power bought from the provider(s) by distributing the controllable loads over time and/or using the ESS to smooth the demand curve.

2.8 Conclusions

New technology, legislation, and pricing policy are currently being developed and implemented on residential electricity markets to enable increased customer participation– one of the objectives of the future grid.

This chapter argues that advanced modeling of residential electricity consumers and an intelligent optimizing algorithm are required to fully achieve the benefits expected from their increased participation. Providing only consumption and/or pricing *information* to the residential electricity consumer and leaving the complex *scheduling problem* to the consumer will result in highly sub-optimal energy utilization.

The proposed modeling framework based on mixed-integer linear programming is presented from a consumer's perspective. The home energy controller derived from this formulation is able to control the various home grid components in order to optimize the household energy use based on the consumer's preferences. This leads to significant economic savings for the consumer compared to the reference case, as well as lower PARs.

Demand response and demand curve flattening achieved by the proposed system will benefit the provider too, by providing an upstream mechanism for reduction or delay in generation reserve and capacity build out.

As the industry moves towards better wind, solar and noncontrollable consumption forecasting, the outcomes of the proposed optimization tool will be further enhanced.

The formulation presented in this chapter can be extended to address real-time demand response at the consumer level. The running times observed would allow for efficiently responding to incentive signals sent every 15 minutes, supporting the implementation of the proposed algorithm.

CHAPTER III

OPTIMAL PRICING ALGORITHM FOR RESIDENTIAL DEMAND RESPONSE USING INVERSE CONVEX OPTIMIZATION

3.1 Introduction

3.1.1 Motivations

Electrical grids are evolving from vertically-integrated physical systems to complex networks of autonomous prosumers exchanging energy and information with each other. *Prosumers* are cyber-physical systems that can simultaneously manage generation, consumption, storage, and/or transmission assets at various spatial and temporal scales [55, 54].

Residential prosumers in particular have gained much attention in recent years as new technology is being deployed downstream of the meter. This includes controllable appliances, distributed generation, storage systems, and scheduling algorithms that can optimize energy utilization in response to dynamic price signals. Residential end-users are becoming active energy players that can collectively impact the operation of the grid through their local decisions.

In this context, electricity providers need to update their models to accurately capture the new internal dynamics of residential end-users. These updated models will allow providers to quantify the value of the end-users' new capabilities to the grid, and better understand how end-users behave when exposed to dynamic price signals.

Under current industry practices, electricity providers typically consider residential demand as an *exogenous* input to the economic dispatch. Additionally, when time-varying pricing policies are in place, price-responsiveness of residential end-users is often modeled as a *memoryless* function of the price.

The inherent dynamics induced by storage and load-shifting capabilities will soon render this modeling approach obsolete. Access to storage and the possibility to defer flexible loads induce an internal state –or memory– in the end-user model [39, 127]. This state corresponds to the amount of backlogged or stored energy; it evolves dynamically over time and depends on the history –and when available, forecast– of electricity prices.

Additionally, home energy management systems [68, 69] enable residential end-users to pursue their own, *local* objectives (e.g. minimizing energy costs) while electricity providers and system operators continue to pursue distinct, *system-level* objectives (e.g minimizing generation costs or enforcing system constraints). In this paradigm shift, dynamic electricity prices are becoming an important means of coordinating the autonomous behavior of residential end-users to the benefit of the overall system.

This chapter proposes a pricing algorithm that captures the end-users' internal dynamics and ensures that, when end-users autonomously optimize their local objectives in response to dynamic prices, they concurrently contribute to optimize the system's objective.

3.1.2 Existing work

The related work in the literature can be classified into two separate groups. A first thread of research focuses on *developing energy optimization algorithms* to be embedded in home energy management systems. These algorithms aim to select the best energy schedule in response to an *exogenous* price signal –either given or predicted. Various techniques have been used to formulate the underlying optimization problem including mixed-integer linear programming [70, 26], particle swarm optimization [57], stochastic optimization [170], optimal stopping rules [169], and genetic algorithms [174].

A second thread of research, closer to our approach in this chapter, focuses on *selecting optimal pricing strategies* for demand response in residential electricity markets [91, 24, 168, 80, 23, 123, 92, 99, 130, 88, 47, 81]. Studies in this second group can be compared with each other and with this chapter across several dimensions (Table 3.1):

3.1.2.1 Temporality

The time horizon considered varies from one to several consecutive time periods. Some authors propose to solve the optimization problem independently for each time slot [24, 168, 23, 92, 130]. Others, including this chapter, account for temporal correlations in the form of initial conditions (modeling past history) and intertemporal constraints (modeling storage and/or load-shifting capabilities) [91, 80, 123, 99, 88, 47, 81].

3.1.2.2 Characteristics of end-user model

A large majority of studies use the concept of *utility* from microeconomics to model the end-user behavior [91, 24, 168, 80, 23, 123, 92, 130, 88, 47, 81]. Although this approach provides valuable theoretical insights, its practical relevance is limited as utility functions are not empirically observable (e.g. [126]). Aggregating utility functions across distinct end-users also raises further theoretical concerns. For these reasons, we choose to *not* use utility functions in this chapter. Some studies, including ours, include specific constraints to model load-shifting capabilities [80, 123, 99, 88, 47]. Additionally, we explicitly model storage, distributed generation, and the ability to sell electricity back to the grid, three energy functions which are typically ignored in most existing works.

Table 3.1: Comparison with recent studies on optimal electricity pricing for demand response

	Framework		Solution method		Time horizon		Temporal correlations		Characteristics of end-user model					Local objective			System objective			Information structure[f]	
	Stackelberg game	Network utility max.	Iterative	Non-iterative	One hour	Several hours	Time-separable[b]	Intertemporal effects[c]	Utility function	Flexible loads	Distributed storage	Distributed generation	Two-way power flows	Cost minimization	Utility maximization	Surplus maximization	Cost minimization	Surplus (profit) max.	Social welfare max.	Complete information	Incomplete information
[91][a]	*			*	*			*	*							*			*	*	
[24]	*			*		*	*		*							*		*		*	
[168]	*			*		*	*		*							*			*	*	
[80]	*			*		*		*	*	*						*		*[d]	*[d]	*	
[23]	*		*		*		*		*							*		*			*
[123]	*		*			*		*	*	*						*		*			*
[92]	*		*		*		*		*						*			*[e]			*
[99]	*		*			*		*		*				*				*			*
[130]		*	*			*	*		*							*			*		*
[88]		*	*			*		*	*	*	*					*			*		*
[47]		*	*			*		*	*	*						*			*		*
[81]		*	*			*		*	*							*			*		*
This chapter	*			*		*		*		*	*	*	*	*			*			*	*

[a] Included for reference.
[b] The optimization problem is solved independently at each time slot.
[c] Accounts for past history and/or intertemporal constraints.
[d] Both objectives are part of the family of objective functions considered.
[e] Revenue maximization (power generation assumed to be fixed).
[f] How much the provider knows of the prosumer's optimization problem.

3.1.2.3 Objective functions

At the local level, most authors assume that end-users maximize their economic surplus [91, 24, 168, 80, 23, 123, 130, 88, 47, 81]. Utility maximization [92] and cost minimization [99] are sometimes considered. At the system level, social welfare maximization [91, 168, 80, 130, 88, 47, 81] and profit maximization [24, 80, 23, 123, 92, 99] are the two most common objectives assumed. In this chapter, we assume that the provider and end-users aim to minimize their respective costs. Cost minimization is the current industry standard when solving the economic dispatch.

3.1.2.4 Modeling framework

A first set of studies [91, 24, 168, 80, 23, 123, 92, 99], including this chapter, frame the pricing problem as a *Stackelberg game* where the provider plays the role of leader, and end-users play roles of followers. For every pricing strategy selected by the provider, each end-user determines his optimal consumption strategy. A second set of studies [130, 88, 47, 81] adopt a *network utility maximization* (NUM) approach and use dual decomposition to compute the optimal prices as a by-product.

3.1.2.5 Information structure

Many studies including this chapter assume that the provider has full knowledge of the end-users optimization problems (including their payoff functions) [91, 24, 168, 80]. We refer to this situation as *complete* information. The extensive literature on non-intrusive load monitoring (NILM) supports this assumption. NILM algorithms can determine the operating schedules of individual devices based on analysis of the current and voltage measured at the eletricity meter. This includes transient and steady-state analysis in the time and frequency domains (e.g. [107, 171, 32, 89]). On the contrary, other works assume *incomplete* information [23, 123, 92, 99, 130, 88, 47, 81].

3.1.2.6 Solution method

The pricing algorithms developed in existing works separate into *iterative* and *non-iterative*. Non-iterative solutions use backward induction and require closed-form expressions of the end-user's payoff functions [91, 24, 168, 80]. Iterative solutions use gradient methods [23, 92, 130, 88, 47, 81] (NUM approach), or genetic [99] or simulated annealing [123] algorithms (Stackelberg approach) to guide the price search. Iterative methods do not require complete information, but involve asynchronous message passing between the provider and end-users at each iteration. In general, iterative methods might also not always converge. A recent study emulates the end-users' response centrally to avoid physical message passing, but requires complete information [131]. In this chapter, we adopt a non-iterative approach. However, contrary to the studies using backward induction, we develop a novel method using inverse convex optimization. Discussion and comparison with related work in the inverse optimization literature can be found in Section 3.5.1.

Finally, although a majority of the studies that we reviewed assume a single electricity provider (including this chapter), some authors consider more complex cases with several providers [92, 81].

3.1.3 Summary of contributions

The main contributions of this chapter can be summarized as follows:

- We propose an optimization model that captures the emerging flexible consumption, storage, and generation capabilities of residential end-users as well as the ability to buy from *and* sell electricity to the provider. Existing models are usually limited to flexible consumption and do not account for bidirectional power flows.

- In particular, for any given end-user, we provide a sufficient constraint that allows modelling an arbitrary number of flexible loads with only one decision variable per time period. Existing models require one variable per time period *per flexible load*.

- We propose an economic dispatch model that explicitly accounts for end-users' internal dynamics. Existing models treat residential demand as an exogenous input. We propose to solve this enhanced economic dispatch in a distributed way using multi-level primal decomposition to both reduce the size of the problem and increase end-user privacy protection. To this end, we aggregate and disaggregate consumption, storage and generation capabilities across clusters of residential end-users.

- We propose a non-iterative pricing algorithm using convex programming and inverse linear programming. Different from existing non-iterative algorithms, our approach does not use backward induction and does not require closed-form expressions. To the best of our knowledge, this work is the first practical application of inverse linear programming.

- We ensure fairness in billing each end-user according to his contribution towards minimizing the provider's generation costs. Existing studies aim to select a pricing scheme that achieves optimality, but do not address the issue of fairness.

- We present extensive results obtained for two test cases based on historical data that demonstrate the proposed approach. Most existing studies present simulation results for test cases using synthetic data for the end-users.

The rest of this chapter is organized as follows. In Section 3.2, we introduce mathematical formulations for basic energy functions that we subsequently use to model the end-user- and provider-controlled assets. In Section 3.3, we formulate the provider and end-user energy optimization problems. In Section 3.4, we develop a framework to solve the enhanced economic dispatch problem in a decentralized way.

Section 3.5 is the core of the chapter: building on the inverse optimization literature, we develop a theoretical framework to select electricity prices that incentivize residential end-users to adopt power schedules that benefit the operation of the overall system. The issue of fairness is addressed in Section 3.6, and numerical results are presented in Section 3.7.

3.2 Preliminaries

In this section, we introduce models for three basic energy functions: controllable generation, energy storage and flexible consumption. These models will serve as building blocks to formulate the provider and end-user optimization problems.

3.2.1 System definition: space and time

Consider a dispatch area $\mathcal{A}$ operated by a single electricity provider. Within $\mathcal{A}$, the provider operates power generators indexed by $i \in I$, large-scale energy storage systems indexed by $l \in L$, and exchanges electricity with residential end-users indexed by $j \in J$. The provider is also in charge of maintaining power balance in $\mathcal{A}$.

Continuous time is approximated as $T+1$ consecutive time periods t. Time period 0 ends at time 0; it is used to provide information about the starting configuration of the system. The power planning and electricity pricing is done for time periods 1 through T. Let $\mathcal{T} \triangleq \{1, ..., T\}$ be the time horizon. Within each time period, all power generation, charging, discharging, delivery, usage, and prices do not vary.

3.2.2 Controllable generation

Consider a controllable generator i. For each time period t, the operating cost is modeled as a convex piecewise-linear function $f_{i,t}$ of the generator power output (Fig.3.1); $f_{i,t}$ reflects primarily the fuel cost necessary to produce electrical energy, but may also reflect other costs (regulatory, environmental, etc.). We call *power production levels* $k \in \{1, 2, ..., K_{i,t}\}$ the breakpoints in $f_{i,t}$, with $K_{i,t}$ the number of breakpoints. The locations and number of breakpoints are specific to each generator. Let $a_{i,k,t}$ be the cost of running generator i at power level k during time period t, and let $b_{i,k,t}$ be the amount of electric energy produced by generator i if run at power level k during period t. By convention, $b_{i,0,t}$ represents the minimum-run production required to maintain generator i online during time t, and $a_{i,0,t}$ represents the corresponding cost.

Denote by $C_{i,t}$ the operating cost, $P_{i,t}$ the power output, and $\mathcal{M}_{i,t}$ the operating point during time period t:

$$\begin{aligned}
C_{i,t} &\triangleq a_{i,0,t} + \sum_{k=1}^{K_{i,t}} w_{i,k,t}(a_{i,k,t} - a_{i,k-1,t}) \\
P_{i,t} &\triangleq b_{i,0,t} + \sum_{k=1}^{K_{i,t}} w_{i,k,t}(b_{i,k,t} - b_{i,k-1,t}) \\
\mathcal{M}_{i,t} &\triangleq (C_{i,t}, P_{i,t})
\end{aligned}$$

where variable $w_{i,k,t}$ denotes how much generator i is using of electricity productivity from level $k-1$ to k during time period t. If generator i runs at power level k or higher during time period t, then $w_{i,k,t} = 1$. If generator i runs at power level $k-1$ or lower during period t, then $w_{i,k,t} = 0$. Otherwise, $w_{i,k,t}$ is such that $P_{i,t}$ is equal to the power output for generator i during time period t. The initial generation condition is:

$$w_{i,k,0} = W_{i,k,0} : \quad 1 \leq k \leq K_{i,0} \tag{25}$$

where $\{W_{i,k,0}\}_{1 \leq k \leq K_{i,0}}$ are the initial production levels at time 0. Additionally, generator i can use from 0% to 100% of each of its power level slot:

$$0 \leq w_{i,k,t} \leq 1 : \quad 1 \leq t \leq T; 1 \leq k \leq K_{i,t} \tag{26}$$

Note that the proposition $\{\forall t, \forall k_0$, if $w_{i,k_0,t} < 1$, then $\forall k \in \{k_0+1, ..., K_{i,t}\}, w_{i,k,t} = 0\}$ will always be true at optimality when minimizing energy costs because of the convexity of $f_{i,t}$.

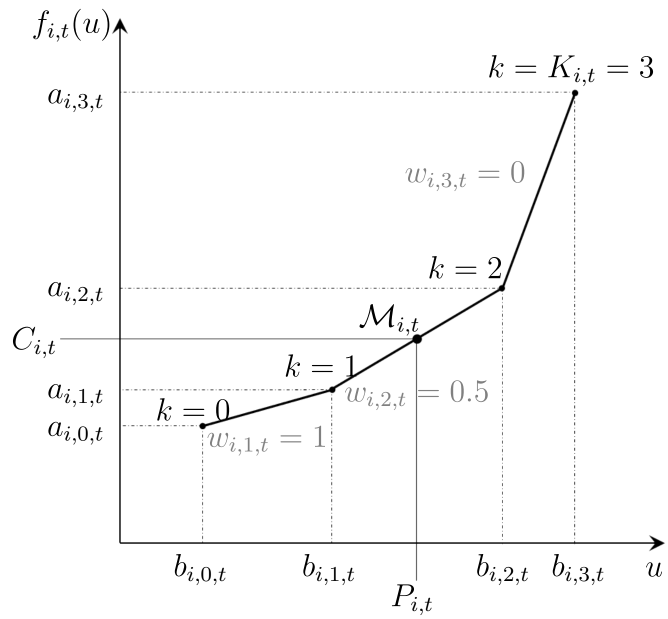


Figure 3.1: Example of generator cost function $f_{i,t}$ and operating point $\mathcal{M}_{i,t}$ with $K_i = 3$, $w_{i,1,t} = 1$, $w_{i,2,t} = 0.5$, $w_{i,3,t} = 0$.

The values of $b_{i,0,t}$ and $b_{i,K_{i,t},t}$ reflect the minimum and maximum generation levels for generator i during each time period t. We also consider the following changeover limits:

$$P_{i,t} - P_{i,t-1} \leq \beta_{i,t}^{max} : \quad 1 \leq t \leq T \tag{27}$$

$$P_{i,t} - P_{i,t-1} \geq -\beta_{i,t}^{min} : \quad 1 \leq t \leq T \tag{28}$$

where $\beta_{i,t}^{max} > 0$ (resp. $\beta_{i,t}^{min} > 0$) is the upper bound (resp. lower bound) on the change in power output from the beginning of period $t-1$ to the beginning of period t.

3.2.3 Energy storage

Consider an energy storage system l. Denote by $s_{l,t}$ the amount of energy stored at the end of period t, $c_{l,t}$ the amount of energy charged during period t, and $d_{l,t}$ the amount of energy discharged during period t. The initial storage condition is:

$$s_{l,0} = s_l^0 \tag{29}$$

with s_l^0 the initial amount of electric energy stored at the beginning of period 1. The amount of energy stored must stay within the system capacity:

$$s_{l,t}^{min} \leq s_{l,t} \leq s_{l,t}^{max} : \quad 1 \leq t \leq T \tag{30}$$

where $s_{l,t}^{max} > 0$ (resp. $s_{l,t}^{min} > 0$) is the maximum (resp. minimum) storage capacity of storage system l at the end of period t. The charging and discharging rates must also stay within the operational limits:

$$0 \leq s_{l,t}^{+} \leq s_{l,t}^{max,+} : \quad 1 \leq t \leq T \tag{31}$$

$$0 \leq s_{l,t}^{-} \leq s_{l,t}^{max,-} : \quad 1 \leq t \leq T \tag{32}$$

where $s_{l,t}^{max,+} > 0$ (resp. $s_{l,t}^{max,-} > 0$) is the maximum charging (resp. discharging) rate for storage system l during time period t.

Finally, the amount of energy stored in storage system l evolves according to:

$$s_{l,t} = \xi_l \cdot s_{l,t-1} + \eta_l \cdot s_{l,t}^{+} - s_{l,t}^{-} : \quad 1 \leq t \leq T \tag{33}$$

where $\xi_l \leq 1$ is the decay factor and $\eta_l \leq 1$ is the roundtrip efficiency factor for storage system l. In general, the factors ξ_l and η_l are complicated functions of the current storage level and past history of the system. In the following, we focus on an ideal case where $\xi_l = 1$ and $\eta_l = 1$.

3.2.4 Flexible consumption

We first introduce a time-shiftable load model widely used in the recent demand response literature to account for schedulable appliances operated by residential end-users (e.g. [104, 26, 175, 168, 25]). Let $\mathcal{A}_j$ be the set of schedulable appliances operated by end-user j. Let $y_{j,a} \triangleq [y_{j,a,1}, ..., y_{j,a,T}]$ be the energy consumption scheduling vector for appliance $a \in \mathcal{A}_j$ where $y_{j,a,t}$ denotes the energy consumption scheduled for a during time period t. Let $y_j \triangleq [y_{j,1}, ..., y_{j,T}]$ be the overall consumption schedule for end-user j formed by stacking up schedules $y_{j,a}$ for all appliances $a \in \mathcal{A}_j$. The set χ_j of feasible consumption schedules y_j for end-user j is:

$$\chi_j = \left\{ y_j \;\middle|\; \forall a \in \mathcal{A}_j, \quad \begin{array}{l} \displaystyle\sum_{t=\alpha_{j,a}}^{\beta_{j,a}} y_{j,a,t} = E_{j,a} \\ y_{j,a,t} = 0, \; \forall t \in \mathcal{T} \backslash \mathcal{T}_{j,a} \\ 0 \leq y_{j,a,t} \leq \gamma_{j,a,t}^{max}, \; \forall t \in \mathcal{T}_{j,a} \end{array} \right\}$$

where $E_{j,a}$ is a pre-determined energy consumption requirement to be allocated to appliance a during $\mathcal{T}_{j,a} \triangleq \{\alpha_{j,a}, ..., \beta_{j,a}\} \subseteq \mathcal{T}$ with $\alpha_{j,a} < \beta_{j,a}$, and $\gamma_{j,a,t}^{max}$ is the maximum power level for appliance a during time period t. Some authors also include minimum power level requirements for each appliance $a \in \mathcal{A}_j$. In this chapter, we model minimum power requirements as fixed consumption requirements. Similarly, the case $\alpha_{j,a} = \beta_{j,a}$ is modeled as fixed consumption requirements using fixed parameters.

The number of decision variables $y_{j,a,t}$ required under this first approach may grow rapidly if end-users operate multiple time-shiftable loads. For reasons discussed in Section 3.5.4, we are interested in limiting the number of end-user variables as much as possible. To this end, we propose an alternative formulation which aggregates energy requirements accross time-shiftable loads while preserving feasibility. Under our approach, for a given user j operating an arbitrary number of time-shiftable loads, only the T variables $y_{j,t}$ are needed.

Let E_{j,t_1,t_2} be the amount of energy required by end-user j from the beginning of period t_1 to the end of period t_2, with $t_1 < t_2$. E_{j,t_1,t_2} is only the requirement associated with time interval $\mathcal{T}_{t_1,t_2} \triangleq \{t_1, .., t_2\}$; it does not include requirements associated with time intervals within or overlapping $\mathcal{T}_{t_1,t_2}$. Let $E_{j,t_1,t_2,t}^{max}$ be the maximum amount of energy that can be allocated during time period $t \in \mathcal{T}_{t_1,t_2}$ to provide for E_{j,t_1,t_2}.

For any $(t_1, t_2) \in \mathcal{T}^2$ with $t_1 < t_2$, let $\mathcal{A}_{j,t_1,t_2} \subseteq \mathcal{A}_j$ be the set of appliances for which $\alpha_{j,a} = t_1$ and $\beta_{j,a} = t_2$. Using the notation above, we have the following relations:

$\forall (t_1, t_2) \in \mathcal{T}^2$ s.t. $t_1 < t_2$,

$$E_{j,t_1,t_2} = \begin{cases} 0 & \text{if } \mathcal{A}_{j,t_1,t_2} \equiv \varnothing \\ \displaystyle\sum_{a \in \mathcal{A}_{j,t_1,t_2}} E_{j,a} & \text{else} \end{cases}$$

$\forall (t_1, t_2, t) \in \mathcal{T}^3$ s.t. $t_1 < t_2$ and $t_1 \leq t \leq t_2$,

$$E^{max}_{j,t_1,t_2,t} = \sum_{a \in \mathcal{A}_{j,t_1,t_2}} \gamma^{max}_{j,a,t}$$

For a given end-user j, for every time interval $\mathcal{T}_{t_1,t_2}$, the total amount of energy consumed by j during $\mathcal{T}_{t_1,t_2}$ is at least the total amount of energy that *must* be consumed by j during that time interval. The latter is the sum of all energy requirements for periods that lie completely within the range t_1 to t_2, including the interval $\mathcal{T}_{t_1,t_2}$ itself:

$$\sum_{t=t_1}^{t_2} y_{j,t} \geq \sum_{t_3=t_1}^{t_3=t_2} \sum_{t_4=t_3}^{t_4=t_2} E_{j,t_3,t_4} : \quad 1 \leq t_1 < t_2 \leq T \tag{34}$$

It is obvious that constraints (34) are necessary for end-user j to satisfy his energy requirements. It is not obvious, but it is true, that these constraints are also sufficient. The proof is given in Appendix 3.9.

Thus, we can redefine the set of feasible consumption schedules y_j for end-user j as:

$$\chi'_j = \left\{ y_j \;\middle|\; \begin{array}{c} \forall (t_1, t_2) \in \mathcal{T}^2 \text{ s.t. } t_1 \leq t_2, \\ \displaystyle\sum_{t=t_1}^{t_2} y_{j,t} \geq \Gamma_{j,t_1,t_2} \\ \forall t \in \mathcal{T}, \quad y_{j,t} \leq y^{max}_{j,t} \end{array} \right\} \tag{35}$$

where:

$$\forall (t_1, t_2) \in \mathcal{T}^2 \text{ s.t. } t_1 \leq t_2, \quad \Gamma_{j,t_1,t_2} \triangleq \sum_{t_3=t_1}^{t_3=t_2} \sum_{t_4=t_3}^{t_4=t_2} E_{j,t_3,t_4}$$

with $\forall t \in \mathcal{T}, E_{j,t,t} = 0$ by convention, and:

$$\forall t \in \mathcal{T}, \qquad y^{max}_{j,t} \triangleq \sum_{\substack{(t_1,t_2) \in \mathcal{T}^2 \\ t_1 < t < t_2}} E^{max}_{j,t_1,t_2,t}$$

Table 3.2: Generic characteristics of the two types of energy players modeled

	Basic Energy Functions				
	Generation		Consumption		Storage
	Controllable	Non-controllable	Flexible	Fixed	
End-user		*	*	*	*
Provider	*	*		*	*

3.3 Energy optimization problems

In this section, we formulate the optimization problem solved by end-users in response to dynamic price signals. We also propose a formulation of the economic dispatch problem that explicitly accounts for the end-users' internal dynamics.

3.3.1 Residential end-users

The end-users' usage requirements can be of two forms: *non-controllable* and *controllable*. Non-controllable usage requires certain amounts of electric power at fixed times (e.g. minimal power requirements of appliances), and/or anytime during a certain period of time but without prior notice (TV, microwave, lights, etc.). Non-controllable usage cannot be scheduled. Let $z_{j,t} \geq 0$ be the fixed power requirement for end-user j during time period t, and define $z_j \triangleq [z_{j,1}, ..., z_{j,T}]$. We assume that z_j can be estimated in advance using historical data.

Controllable usage is more flexible in that it requires, for each controllable load, a certain amount of electrical energy (known in advance) during a certain time interval. This energy can be provided to the load at anytime during that time interval. Controllable loads are therefore schedulable (e.g. dishwasher, washing machine, dryer, water heater, pool pump). Fexible requirements are modeled as shown in Section 3.2.4. In particular, $y_{j,t}$ denotes the amount of power used by end-user j during time period t to meet his flexible usage requirements.

End-users may have the ability to store energy locally. For each end-user j, define $s_j \triangleq [s_{j,1}, ..., s_{j,T}]$ the energy storage schedule, $s_j^+ \triangleq [s_{j,1}^+, ..., s_{j,T}^+]$ the charging schedule, and $s_j^- \triangleq [s_{j,1}^-, ..., s_{j,T}^-]$ the discharging schedule over $\mathcal{T}$. The variables $s_{j,t}$, $s_{j,t}^+$, and $s_{j,t}^-$ follow the model introduced in Section 3.2.3. Temporary storage capabilities (e.g. battery electric vehicle connected to the end-user home grid) are modeled by setting $s_{j,t} = 0$ when not available (e.g. when vehicle is absent).

When residential end-users have the ability to generate electricity locally, their generation capabilities are typically non-controllable (e.g.: small wind turbines, solar panels). Let $p_{j,t} \geq 0$ be the amount of electric energy produced by end-user j during time period t. We assume that $p_{j,t}$ can be estimated in advance using historical data and weather forecast.

Finally, residential end-users have the ability to exchange energy with the provider. The variables $x_{j,t}^+$ and $x_{j,t}^-$ denote the amounts of power purchased from and sold to the provider by end-user j during time period t:

$$0 \leq x_{j,t}^+ \leq x_{j,t}^{max,+} : \quad 1 \leq t \leq T \tag{36}$$

$$0 \leq x_{j,t}^- \leq x_{j,t}^{max,-} : \quad 1 \leq t \leq T \tag{37}$$

where $x_{j,t}^{max,+} > 0$ and $x_{j,t}^{max,-} > 0$ are the upper and lower bounds on the amounts of power that may be purchased and sold by end-user j during time period t. These bounds reflect thermal limits at the point of common coupling, and possibly other limits resulting from contractual terms with the provider.

Define $x_j^+ \triangleq [x_{j,1}^+, ..., x_{j,T}^+]$ and $x_j^- \triangleq [x_{j,1}^-, ..., x_{j,T}^-]$ the buying and selling schedules, $\hat{x}_j \triangleq [x_j^+, x_j^-]$ the exchange schedule, and $\Delta x_j \triangleq x_j^+ - x_j^-$ the net exchange schedule. Also define $\hat{y}_j = [y_j, s_j, s_j^+, s_j^-]$ the internal schedule for end-user j over $\mathcal{T}$.

End-user j must balance his local energy usage for each time period t:

$$
\begin{aligned}
&(y_{jt} + z_{jt}) + (s^+_{j,t} - s^-_{j,t}) - p_{j,t} \\
&\qquad\qquad = (x^+_{j,t} - x^-_{j,t}) : \quad 1 \leq t \leq T
\end{aligned}
\tag{38}
$$

In this chapter, we model residential end-users as cost minimizers. The end-users' goal is to select feasible consumption, storage, purchase and sale schedules that minimize their energy costs over $\mathcal{T}$. We formulate the underlying optimization problem as a linear program:

$$
\text{(P-j)} \qquad
\begin{aligned}
&\textbf{minimize} && \Psi_j = \sum_{t=1}^{T} (\pi^+_{jt} x^+_{jt} + \pi^-_{jt} x^-_{jt}) \\
&\textbf{subject to} && A_j x_j \leq b_j, x_j \geq 0
\end{aligned}
$$

with:

- $\pi^+_{j,t} > 0$: the price the provider offers to sell electricity to end-user j during t,
- $\pi^-_{j,t} < 0$: the price the provider offers to purchase electricity from end-user j during t,
- $x_j \triangleq (\hat{x}_j, \hat{y}_j)$: the power schedule for end-user j's assets,
- $\mathscr{P}_j \triangleq \{x_j \in \mathbb{R}^m : A_j x_j \leq b_j, x_j \geq 0\}$: the polytope defined by constraints {(29)-(33), (35)-(38)}.

In other words, we assume that end-user j's home energy management system solves (P-j) to select the best energy schedule. The program (P-j) has $m = 6T + 1$ variables, and $m' = 0.5T^2 + 15.5T + 2$ constraints.

Define $\pi^+_j \triangleq (\pi^+_{j,1}, ..., \pi^+_{j,T})$, $\pi^-_j \triangleq (\pi^-_{j,1}, ..., \pi^-_{j,T})$, and $\pi_j \triangleq (\pi^+_j, \pi^-_j)$. Also define $c_j \triangleq (\pi_j, 0, ..., 0)$ such that $\Psi_j = c_j x_j$.

3.3.2 Electricity provider

The generators $i \in I$ available for dispatch between time 0 and the end of period T are modeled as shown in Section 3.2.2. In addition, let $G_t > 0$ be the non-controllable generation injected into the electricity system within the boundaries of $\mathcal{A}$ during time period t. This includes pre-committed production (bilateral contracts), reliability must-run production and intermittent or must-take resources (solar, wind, run-of-river hydro).

The large-scale storage systems $l \in L$ operated by the provider are modeled as shown in Section 3.2.3. For a given storage system $l \in L$, define $S_l \triangleq [S_{l,1}, ..., S_{l,T}]$ the energy storage schedule, $S_l^+ \triangleq [S_{l,1}^+, ..., S_{l,T}^+]$ the charging schedule, and $S_l^- \triangleq [S_{l,1}^-, ..., S_{l,T}^-]$ the discharging schedule over $\mathcal{T}$.

The provider exchanges energy with end-users $j \in J$ through the electricity network. For simplicity, we model the network as a single infinite bus without losses. Additionally, let $D_t > 0$ be the non-controllable demand during time period t, including bilateral contracts with large industrial end-users.

Finally, power balance must be maintained within area $\mathcal{A}$ for each time period t:

$$\begin{aligned} \sum_{i \in I} P_{i,t} - \sum_{l \in L} (S_{l,t}^+ - S_{l,t}^-) + (G_t - D_t) \\ = \sum_{j \in J} (x_{j,t}^+ - x_{j,t}^-) : \quad 1 \leq t \leq T \end{aligned} \tag{39}$$

Under the standard economic dispatch approach, the provider selects feasible generation schedules that minimize generation costs while meeting the end-users demand modeled as an exogenous input to the problem.

In this chapter, we initially assume that the end-users are working cooperatively with the provider to optimize the provider's objective over $\mathcal{T}$; we refer to the optimal objective achieved as the *team optimum*. The corresponding optimization problem – which we subsequently refer to as the *enhanced economic dispatch* or *master problem*– can also be formulated as a linear program:

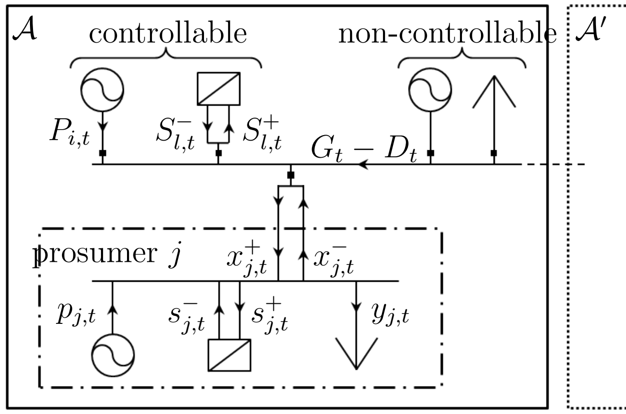


Figure 3.2: System modeling of the provider-controlled and prosumer-controlled assets within dispatch area $\mathcal{A}$

$$
\text{(MP)} \qquad \begin{array}{ll} \textbf{minimize} & \Phi_{\mathcal{A}} = \sum_{i \in I} \sum_{t=1}^{T} C_{i,t} \\ \textbf{subject to} & Ax \leq b, x \geq 0 \end{array}
$$

with:

- x : the power schedule for both the provider-controlled, and prosumer-controlled assets,
- $\mathscr{P}_{\mathcal{A}} \triangleq \{x \in \mathbb{R}^n : Ax \leq b, x \geq 0\}$: the polytope defined by constraints $\{$(25)-(28)$\}$ (controllable generation, for all $i \in I$), $\{$(29)-(33)$\}$ (large-scale storage, for all $l \in L$), $\{$(35)-(38)$\}$ (end-users-controlled assets, for all $j \in J$), and (39) (network power balance).

The program (MP) has $n = (6T+1)|J|+(3T+1)|L|+\sum_{i\in I}\sum_{t=0}^{T} K_{i,t}$ variables and $n' = (0.5T^2+15.5T+2)|J|+(8T+2)|L|+2T|I|+2\sum_{i\in I} K_{i,0}+2\sum_{i\in I}\sum_{t=1}^{T} K_{i,t}+2T$ constraints.

In reality, end-users do *not* work cooperatively with the provider but instead autonomously select their best strategy in response to dynamic price signals. Recall that, similarly to [91, 24, 168, 80, 23, 123, 92, 99], we frame the pricing problem as a Stackelberg game where the provider plays the role of leader, and end-users play roles of followers. For every pricing strategy selected by the provider, each end-user determines his optimal consumption strategy. Since the sets of actions of the provider (pricing schemes) and end-users (energy schedules) are compact, and the payoff functions $\Phi_{\mathcal{A}}$ and Ψ_j are continuous, the Stackelberg equilibrium always exists. The best solution the provider can possibly achieve in this Stackelberg game is precisely the team optimum obtained when solving (MP).

The central part of the problem is then to choose a pricing scheme that induces the end-users to behave cooperatively, and thus achieve the team optimum. More precisely, denote by $x^\star \in argmin_x\{\Phi_{\mathcal{A}} : Ax \leq b\}$ the optimal solution obtained when solving (MP). For any pricing scheme π_j, end-user j finds an optimal schedule $x_j^{\star} \in argmin_x\{\Psi_j : A_j x_j \leq b_j\}$. The goal of the provider is to find a particular π_j such that end-user j can be induced to act cooperatively, i.e. select an energy exchange schedule $\hat{x}_j^{\star}$ as close as possible to $\hat{x}_j^\star$ to achieve the team optimum. Note that the internal power schedule $\hat{y}_j^{\star}$ does not directly impact the provider's operations, therefore $\hat{y}_j^{\star}$ may differ from $\hat{y}_j^\star$.

3.4 Multi-level decomposition of enhanced economic dispatch

In this section, we develop a method to solve the enhanced economic dispatch in a distributed way using multi-level primal decomposition.

3.4.1 Hierachical control structure

Solving the master problem (MP) as formulated in Section 3.3.2 allows us to determine in a single step the desired energy exchange schedules $\hat{x}_j^\star$ for each residential end-user –or *prosumer*– $j \in J$. This formulation corresponds to a flat representation of area $\mathcal{A}$ (Fig. 3.3a).

Three factors can motivate the decomposition of the master problem into distributed subproblems: computational cost, data size requirements, and end-user privacy. Solving (MP) can become computationally expensive as the size of $\mathscr{P}_{\mathcal{A}}$ increases. In particular, the number of rows in A increases with $T^2|J|$, where $|J|$ is the number of residential prosumers in J. Decomposition allows for reducing the size of $\mathscr{P}_{\mathcal{A}}$ through sequential data aggregation, which in turn reduces the amount of data eventually transfered to the central operator. Data aggregation also increases end-user privacy protection.

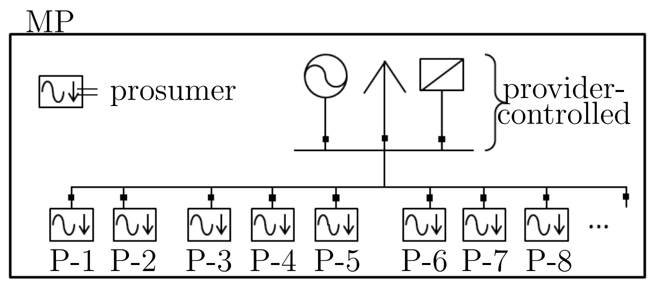
In practice, we propose to decompose the master problem (MP) into distributed subproblems (SP-x) modeling nested super-prosumers (Fig. 3.3b). A *super-prosumer* x is a virtual prosumer formed by aggregating the consumption, production and storage capabilities of other prosumers. These capabilities are placed under a single objective function. This operation can be repeated, and the capabilities of several super-prosumers can be aggregated to form a new, larger super-prosumer.

The resulting control structure is a multi-level hierarchical tree where distributed problems are coordinated by other distributed problems at the above level, and eventually by the master problem (Fig. 3.3c). The master problem can be decomposed arbitrarily, or following the network topology of area $\mathcal{A}$ (transformers, substations, etc.). In the later case, the actual computation may be distributed, each (SP-x) being solved locally and their output passed down to the next level, or centralized, all (SP-x) being solved at the same node.

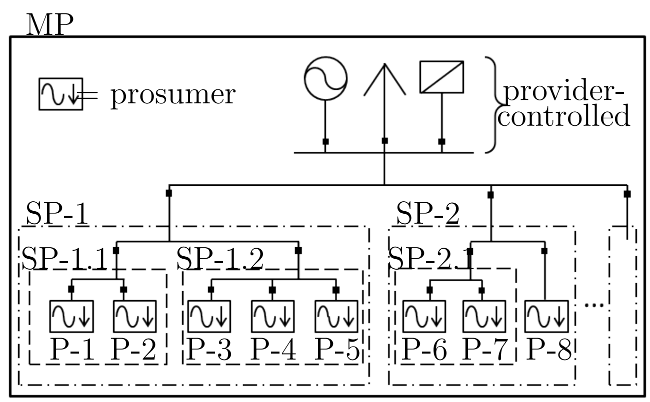
3.4.2 Aggregation of prosumers

Let J_{x} be the set of prosumers aggregated to form super-prosumer x. Super-prosumers *are* prosumers, and can therefore be modeled using the same parameters and variables.

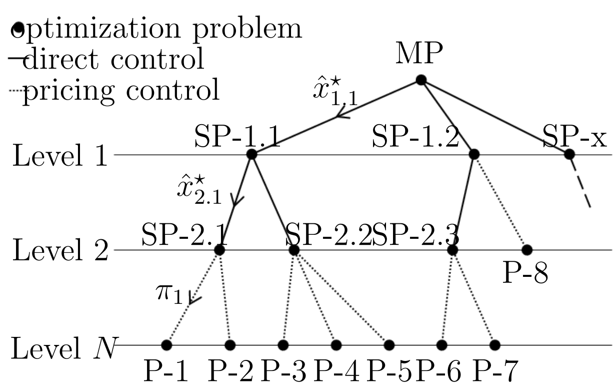
Denote by $p_{\mathrm{x},t}$ the amount of electric energy produced by super-prosumer x during



(a) Flat representation of dispatch area $\mathcal{A}$



(b) Nested representation of dispatch area $\mathcal{A}$ using super-prosumers



(c) Hierarchical control structure for dispatch area $\mathcal{A}$

Figure 3.3: Multi-level decomposition of master problem (MP) into subproblems (SP-x) and prosumer problems (P-j) with $N = 3$ for dispatch area $\mathcal{A}$

time period t, E_{x,t_1,t_2} the amount of energy required by x from the beginning of period t_1 to the end of period t_2, and $E^{max}_{\mathrm{x},t_1,t_2,t}$ the maximum amount of energy that can be allocated during any time period from the beginning of period t_1 to the end of period t_2 in order to provide for E_{x,t_1,t_2}. Also define $x^{max,+}_{\mathrm{x},t}$ and $x^{max,-}_{\mathrm{x},t}$ the upper and lower bounds on the amounts of energy that may be purchased and sold by super-prosumer x.

Aggregating the production, consumption, and energy exchange parameters across prosumers in J_{x} is an additive operation:

$$
\begin{aligned}
p_{\mathrm{x},t} &\triangleq \sum_{j\in J_{\mathrm{x}}} p_{j,t} &&: \quad 1 \leq t \leq T \\
E_{\mathrm{x},t_1,t_2} &\triangleq \sum_{j\in J_{\mathrm{x}}} E_{j,t_1,t_2} &&: \quad 1 \leq t_1 < t_2 \leq T \\
E^{max}_{\mathrm{x},t_1,t_2,t} &\triangleq \sum_{j\in J_{\mathrm{x}}} E^{max}_{j,t_1,t_2,t} &&: \quad 1 \leq t_1 \leq t \leq t_2 \leq T \\
x^{max,+}_{\mathrm{x},t} &\triangleq \sum_{j\in J_{\mathrm{x}}} x^{max,+}_{j,t} &&: \quad 1 \leq t \leq T \\
x^{max,-}_{\mathrm{x},t} &\triangleq \sum_{j\in J_{\mathrm{x}}} x^{max,-}_{j,t} &&: \quad 1 \leq t \leq T
\end{aligned}
$$

Aggregating storage capabilities across J_{x} while preserving feasibility is less straightforward as the charging and discharging rates may differ significantly from one storage system to another. For this reason, we assume in the following that the storage variables and constraints are carried over to the upper level when aggregating.

Assuming an extreme case where the $|J|$ initial prosumers would eventually be aggregated into one unique super-prosumer at level 1, the matrix A would now have $n_1 = 3T + (3T+1)|J| + (3T+1)|L| + \sum_{i\in I}\sum_{t=0}^{T} K_{i,t}$ variables (i.e. $3T(|J|-1)$ less than initially), and $n'_1 = (0.5T^2+8.5T)+(8T+2)|J|+(8T+2)|L|+2T|I|+\sum_{i\in I} K_{i,0}+2\sum_{i\in I}\sum_{t=1}^{T} K_{i,t}$ constraints (i.e. $(0.5T^2+7.5T)(|J|-1)$ less than initially). When $|J| >> |I|, |L|, T$ (which we expect in practice) $n_1/n \approx 50\%$ and $n'_1/n' \approx 16/(T+31)$. For $T = 24$, $n'_1/n' \approx 29\%$, i.e. a reduction of the number of variables by 50%, and of the number of rows in A by 71%.

3.4.3 Propagation of control signals

The master problem (MP) assigns energy schedules $\hat{x}_{\mathrm{x}}^{\star}$ to each of the level-1 super-prosumers (Fig. 3.3c). Each super-prosumer x subsequently determines the exchange schedules assigned to the level-2 (super-)prosumers $j \in J_{\mathrm{x}}$ by solving the following program:

$$
\text{(SP-x)} \qquad \begin{array}{lll} \textbf{minimize} & \|\sum_{j \in J_{\mathrm{x}}} \Delta x_j - \Delta x_{\mathrm{x}}^{\star}\| & \\ \textbf{subject to} & A_j x_j \leq b_j & \forall j \in J_{\mathrm{x}} \end{array}
$$

This process iterates until a desired power exchange schedule $\hat{x}_j^{\star}$ has been assigned to each residential prosumer $j \in J$.

3.5 *Optimal pricing: theoretical framework*

In this section, we propose a method to select the electricity prices π_j such that each prosumer $j \in J$ responds with a power exchange schedule $\hat{x}_j^{\star}$ as close as possible to $\hat{x}_j^{\star}$.

3.5.1 Related work

Setting the prices π_j can be viewed as an inverse optimization problem. The "forward" optimization problem (P-j) consists of finding a feasible power schedule x_j such that the objective $\Psi_j = c_j x_j$ is optimal at x_j. The corresponding inverse optimization problem consists of finding a cost vector $c_j = (\pi_j, 0, ..., 0) \in \mathbb{R}^m$ that makes a given schedule x_j^0 optimal to problem (P-j). In our particular case, $x_j^0 = x_j^{\star}$, and (P-j) is a linear program.

Ahuja and Orlin developed a general approach to solve inverse linear programming problems under the weighted L_1 and L_∞ norms (see [3]), building on earlier work by Zhang and Liu ([172], [173]). In these papers, inverse linear programming is understood as minimally adjusting the cost coefficients of a linear program such that a given feasible solution becomes an optimal solution under the new cost coefficient values.

Our own approach differs in a number of ways. First, and contrary to what the above references seem to suggest, it is worth noting that *any* feasible solution cannot necessarily be made optimal. Indeed, only those feasible solutions that are *also* on the surface (faces, edges, vertices) of the linear program's feasible region –a convex polytope– can be made optimal. Conversely, the feasible solutions located in the interior of the polytope cannot be made optimal, unless one allows the cost coefficients to be all zeros, which is of limited interest for practical applications. In our particular case, this means that only those feasible power schedules x_j that are on the surface of $\mathscr{P}_j$ can possibly be made optimal.

Second, the general approach developed by Ahuja and Orlin does not consider the case where all or part of the cost coefficients must verify some pre-specified constraints. In our case, while the first $2T$ components of c_j are the prices $\pi^+_{j,t}$ and $\pi^-_{j,t}$, the remaining cost coefficients must be set to zero. These zero cost coefficients correspond to the prosumer's internal storage and consumption variables that do not appear in Ψ_j. Additionally, we must require that $\pi^+_{j,t}$ be strictly positive, $\pi^-_{j,t}$ be strictly negative, $\pi^+_{j,t}$ and $|\pi^-_{j,t}|$ be less than or equal to some price cap $\pi^{max} > 0$, and that arbitrage is not permitted at the end-user level. We denote by $\mathscr{C}$ the set of cost vectors $c_j \in \mathbb{R}^m$ satisfying these restrictions:

$$\mathscr{C} \triangleq \left\{ \left(\sum_{t=1}^{2T} \mu_t e_t \right) \in \mathbb{R}^m \;\middle|\; \forall t \in (1,T), \quad \begin{aligned} 0 < \mu_t \leq \pi^{max} \\ -\pi^{max} \leq \mu_{t+T} < 0 \\ 0 < (\mu_t + \mu_{t+T}) \end{aligned} \right\}$$

with $(e_t)_{1 \leq t \leq m}$ the canonical basis for $\mathbb{R}^m$. On the other hand, while Ahuja and Orlin's approach seeks a new cost vector that remains as close as possible to some pre-specified cost vector, we do not have such a requirement in our particular case.

Third, for a given power schedule x_j^0, finding a cost vector $c_j^0 \in \mathscr{C}$ such that $x_j^0 \in argmin_{x_j}\{c_j^0 x_j : A_j x_j \leq b_j\}$, that is, "making x_j^0 optimal" in Ahuja and Orlin's terms, would not necessarily lead prosumer j to select x_j^0 in response to c_j because of cases of multiple optima in the primal (faces of $\mathscr{P}_j$). Instead, ideally, we would like to find $c_j^0 \in \mathscr{C}$ such that $argmin_{x_j}\{c_j^0 x_j : A_j x_j \leq b_j\} = \{x_j^0\}$, which is a stronger requirement than in Ahuja and Orlin's formulation.

Finally, while finding a cost vector $c_j^0 \in \mathscr{C}$ such that $argmin_{x_j}\{c_j^0 x_j : A_j x_j \leq b_j\} = \{x_j^\star\}$ would satisfy the provider's requirements, recall that the provider only requires the energy exchange schedule $\hat{x}_j^{\star}$ selected by the end-user to be as close as possible to $\hat{x}_j^\star$. Let $\hat{x}_j^\star \in \mathbb{R}^{2T}$ be the subvector equal to the first $2T$ components of $x_j^\star$. In polyhedral terminology, $(\hat{x}_j^\star, 0, ..., 0) \in \mathbb{R}^m$ is the *projection* of $x_j^\star \in \mathbb{R}^m$ onto the lower dimensional space of interest to the provider. In the following, we simply say for brevity that $\hat{x}_j^\star$ is the projection of $x_j^\star$.

3.5.2 Basic concepts: exposability, unique exposability

We begin by defining the following terms:

Definition 1. *$x_j^0 \in \mathscr{P}_j$ is exposable for (P-j) if and only if there exists $c_j^0 \neq 0$ such that $x_j^0 \in argmin_{x_j}\{c_j^0 x_j : A_j x_j \leq b_j\}$. Such a c_j^0 is said to expose x_j^0.*

Definition 2. *$x_j^0 \in \mathscr{P}_j$ is uniquely exposable for (P-j) if and only if there exists c_j^0 such that $argmin_{x_j}\{c_j^0 x_j : A_j x_j \leq b_j\} = \{x_j^0\}$. Such a c_j^0 is said to uniquely expose x_j^0.*

We also define terminology for situations where we impose constraints on c_j^0.

Definition 3. *$x_j^0 \in \mathscr{P}_j$ is $\mathscr{C}$-exposable for (P-j) if and only if there exists $c_j^0 \in \mathscr{C}$ that exposes x_j^0.*

Definition 4. *$x_j^0 \in \mathscr{P}_j$ is uniquely $\mathscr{C}$-exposable for (P-j) in the strong sense if and only if there exists $c_j^0 \in \mathscr{C}$ that uniquely exposes x_j^0. Such a c_j^0 is said to uniquely expose x_j^0 in the strong sense.*

We sometimes use the term $\mathbb{R}^m$-exposable to mean exposable, to emphasize the absence of constraints on c_j^0 except $c_j^0 \neq 0$. In Ahuja and Orlin's terms, "to make x_j^0 an optimal solution" means "to make x_j^0 $\mathbb{R}^m$-exposable". Similarly, "c_j^0 is inverse feasible with respect to x_j^0" means "c_j^0 exposes x_j^0" using our terminology.

By a well-known property of polyhedra, for $c_j^0 \in \mathscr{C}$ to uniquely expose a given $x_j^0 \in \mathscr{P}_j$ in the strong sense, x_j^0 must be a vertex, or extreme point, of $\mathscr{P}_j$. However, in our problem, $x_j^\star$ is *not* necessarily an extreme point of $\mathscr{P}_j$, in which case such c_j^0 simply does not exist. We need a strategy to deal with this case.

One strategy is to find an extreme point of $\mathscr{P}_j$ as close as possible to $x_j^\star$, and try to uniquely expose that point as an acceptable proxy. We show in Appendix 3.10 that, even when no constraints are placed on the cost vector (unique $\mathbb{R}^m$-exposability), finding an extreme point of a polyhedron closest to a given point is in general strongly NP-complete. Since the provider is only concerned with the energy flows between itself and the prosumers, we could seek to meet the following weaker property.

Definition 5. *$x_j^0 \in \mathscr{P}_j$ is uniquely $\mathscr{C}$-exposable for (P-j) in the weak sense if and only if there exists $c_j^0 \in \mathscr{C}$ such that $\forall x_j^1 \in argmin_{x_j}\{c_j^0 x_j : A_j x_j \leq b_j\}$ it is true that $\hat{x}_j^1 = \hat{x}_j^0$. Such a c_j^0 is said to uniquely expose x_j^0 in the weak sense.*

Since unique exposability in the weak sense is sufficient to meet the provider's requirements, another strategy is to seek an extreme point $x_j^{\star}$ whose projection $\hat{x}_j^{\star}$ onto the lower dimensional space is the same as $\hat{x}_j^\star$, the projection of $x_j^\star$ (Fig. 3.4). We show in Appendix 3.11 that in general finding such $x_j^{\star}$ is strongly NP-complete.

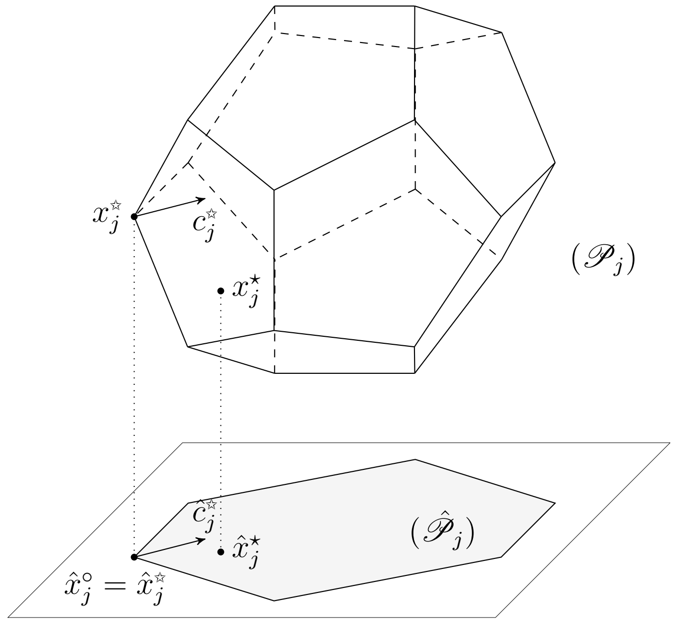


Figure 3.4: Three-dimensional (arbitrary) representation of polytopes $\mathscr{P}_j$ and $\hat{\mathscr{P}}_j$.

3.5.3 Overview of proposed approach

Intuitively, the linear constraints placed on the cost vector are relatively more stringent in $\mathbb{R}^m$ than in the $2T$-dimensional space of interest to the provider. This is because the $(m - 2T)$ cost coefficients correponding to the prosumer's internal variables must be set to zero in $\mathbb{R}^m$ while the constraints affecting the $2T$ prices remain the same, making it possibly harder to achieve unique exposability in the full dimensional space. Preliminary simulations on small test cases confirmed this intuition.

For this reason, we first tackle the inverse optimization problem in the lower dimensional space. We calculate the projection of the end-user's polytope $\mathscr{P}_j$ onto the $2T$-dimensional space of interest to the provider, and find an initial cost vector using strong duality. This cost vector guides the search for a proxy extreme point close to $\hat{x}_j^\star$. We then find a cost vector that uniquely exposes this proxy extreme point in the lower dimensional space.

In a second phase, we return to the full dimensional space. We show that the prices selected in the lower dimensional space uniquely expose an extreme point of

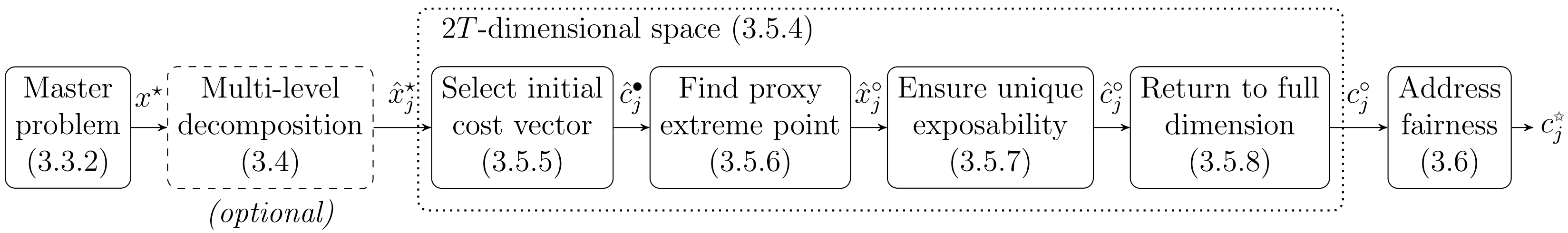


Figure 3.5: Sequential process to find $(c_j^{\star}, x_j^{\star}) \in \mathscr{C} \times \mathscr{P}_j$ for a given $x_j^\star \in \mathscr{P}_j$.

$\mathscr{P}_j$ whose projection onto the lower dimensional space *is* the proxy point close to $\hat{x}_j^\star$ that we previously identified.

In a final phase, we conduct post-treament operations on the prices selected to maintain some degree of fairness between the end-users. We also adjust the power schedules for the provider-controlled assets based on the end-user schedules to be uniquely exposed to ensure power balance is maintained within area $\mathcal{A}$. Fig. 3.5 summarizes the proposed approach.

3.5.4 Computing the projection of $\mathscr{P}_j$

Let $\hat{\mathscr{P}}_j \subseteq \mathbb{R}^{2T}$ be the projection of $\mathscr{P}_j$ onto the lower dimensional space of interest to the provider:

$$\hat{\mathscr{P}}_j \triangleq \{\hat{x}_j \in \mathbb{R}^{2T} \mid \exists \hat{y}_j \in \mathbb{R}^{(m-2T)}, (\hat{x}_j, \hat{y}_j) \in \mathscr{P}_j\}$$

In this section, we present the step-by-step process by which we successively eliminate the variables $s_{j,t}$, $s^+_{j,t}$, $s^-_{j,t}$, and $y_{j,t}$ from the known representation of $\mathscr{P}_j$ to obtain a representation of $\hat{\mathscr{P}}_j$, for any $j \in J$.

Recall that $\mathscr{P}_j$ is defined by the system of constraints {(29)-(33), (35)-(38)}. Combining (29), (33) and (38), we obtain:

$$s_{j,t} = \sum_{i=1}^{t}(s^+_{j,i} - s^-_{j,i}) + s^0_j \qquad : \quad 1 \leq t \leq T$$

$$s^+_{j,t} = x^+_{j,t} - x^-_{j,t} - y_{j,t} - z_{j,t} + s^-_{j,t} + p_{j,t} \qquad : \quad 1 \leq t \leq T$$

Eliminating $s_{j,t}$ and $s^+_{j,t}$ from (30) and (31) using the expressions above, we obtain:

$\forall t \in (1, T)$,

$$s^{min}_{j,t} \leq \sum_{i=1}^{t}(x^+_{j,i} - x^-_{j,i} - y_{j,i} - z_{j,i} + p_{j,i}) \leq s^{max}_{j,t} \tag{40}$$

$$0 \leq x^+_{j,t} - x^-_{j,t} - y_{j,t} - z_{j,t} + s^-_{j,t} + p_{j,t} \leq s^{max,+}_{j,t} \tag{41}$$

Eliminating $s^-_{j,t}$ from constraints (32) and (41) using the Fourier-Motzkin elimination method, we obtain:

$\forall t \in (1, T)$,

$$-x^{+}_{jt} + x^{-}_{jt} + y_{j,t} + z_{j,t} \leq s^{max,-}_{j,t} + p_{j,t} \tag{42}$$

$$x^{+}_{jt} - x^{-}_{jt} - y_{j,t} - z_{j,t} \leq s^{max,+}_{j,t} - p_{j,t} \tag{43}$$

Some of the time periods $t \in \mathcal{T}$ may not have flexible requirements. Therefore, some of the $y_{j,t}$ variables may be unnecessary. Thus, let us first simplify the system of constraints before eliminating the remaining $y_{j,t}$ using Fourier-Motzkin.

Consider a residential end-user $j \in J$. Let $\mathcal{F}_{j,i} = \{a_{j,i}, ..., b_{j,i}\}$ be the sets of consecutive time periods with flexible consumption requirements indexed by $i \in F_j$, with:

$$\forall i \in F_j, \quad (a_{j,i}, b_{j,i}) \in \mathcal{T}^2$$

$$\forall i \in \{1, ..., |F_j| - 1\}, \quad a_{j,i} < b_{j,i} < b_{j,i} + 1 < a_{j,i+1} < b_{j,i+1}$$

The condition $b_{j,i} + 1 < a_{j,i+1}$ means that there is at least one time period without flexible consumption requirements between two consecutive sets $\mathcal{F}_{j,i}$ and $\mathcal{F}_{j,i+1}$.

For end-user j, define:

- $\tau_{j,1} \triangleq \mathcal{T} \backslash \bigcup_{i \in F_j} \mathcal{F}_{j,i}$: the set of time periods t without flexible consumption requirements;
- $\tau_{j,2} \triangleq \bigcup_{i \in F_j} \mathcal{F}_{j,i}$: the set of time periods t with flexible consumption requirements;
- $\tau_{j,3}$: the set of pairs $(t_1, t_2) \in \mathcal{T}^2$ s.t. $E_{j,t_1,t_2} \neq 0$;
- $\tau_{j,4} \triangleq \{a_{j,1}, a_{j,2}, .., a_{j,|F_j|}\}$: the set of first time periods for each $\mathcal{F}_{j,i}$;
- $\tau_{j,5} \triangleq \bigcup_{i \in F_j} \{a_{j,i+1}, ..., b_{j,i}\} = \tau_2 \backslash \tau_4$;
- $\tau_{j,6} \triangleq \{b_{j,1}, b_{j,2}, .., b_{j,|F_j|}\}$: the set of last time periods for each $\mathcal{F}_{j,i}$;

Variables $\{y_{j,t}\}_{t\in\tau_{j,1}}$ are unnecessary since no flexible consumption requirements are specified for time periods in $\tau_{j,1}$. Thus, we only keep variables $\{y_{j,t}\}_{t\in\tau_{j,2}}$. Additionally, the terms $\sum_{i=1}^{t} y_{j,i}$ in (40) lead us to define the following change of variable: $\forall t \in \tau_{j,2},\ Y_{j,t} \triangleq \sum_{k=a_i}^{t} y_{j,k}$ where $i \in F_j$ is such that $t \in \mathcal{F}_{j,i}$.

With these new variables, constraints (35) become: $\forall (t_1,t_2) \in \tau_{j,3}$,

$$\begin{cases} Y_{j,t_2} \geq \Gamma_{j,t_1,t_2} & \text{if } t_1 = a_i \qquad (44) \\ Y_{j,t_2} - Y_{j,t_1} \geq \Gamma_{j,t_1,t_2} & \text{else} \qquad (45) \end{cases}$$

where $i \in F_j$ is such that $(t_1,t_2) \in \mathcal{F}^2_{j,i}$, and:

$$\forall t \in \tau_{j,4}, \qquad 0 \leq Y_{j,t} \leq y^{max}_{j,t} \tag{46}$$

$$\forall t \in \tau_{j,5}, \qquad 0 \leq Y_{j,t} - Y_{j,t-1} \leq y^{max}_{j,t} \tag{47}$$

Constraints (40) become:

$$\begin{aligned} \forall t \in \tau_{j,1}, \quad s^{min}_{j,t} \leq & \sum_{i=1}^{t}(x^+_{j,i} - x^-_{j,i} + p_{j,i} - z_{j,i}) \\ & - \sum_{\substack{b_i \in \tau_{j,6} \\ b_i < t}} Y_{j,b_i} + s^0_j \leq s^{max}_{j,t} \end{aligned} \tag{48}$$

$$\begin{aligned} \forall t \in \tau_{j,2}, \quad s^{min}_{j,t} \leq & \sum_{i=1}^{t}(x^+_{j,i} - x^-_{j,i} + p_{j,i} - z_{j,i}) \\ & - \sum_{\substack{b_i \in \tau_{j,6} \\ b_i < t}} Y_{j,b_i} - Y_{j,t} + s^0_j \leq s^{max}_{j,t} \end{aligned} \tag{49}$$

Constraints (42) become:

$$\forall t \in \tau_{j,1}, -x^+_{jt} + x^-_{jt} \leq s^{max,-}_{j,t} - z_{j,t} + p_{j,t} \tag{50}$$

$$\forall t \in \tau_{j,4}, -x^+_{jt} + x^-_{jt} + Y_{j,t} \leq s^{max,-}_{j,t} - z_{j,t} + p_{j,t} \tag{51}$$

$$\forall t \in \tau_{j,5},$$

$$- x^+_{jt} + x^-_{jt} + Y_{j,t} - Y_{j,t-1} \leq s^{max,-}_{j,t} - z_{j,t} + p_{j,t} \tag{52}$$

Constraints (43) become:

$$\forall t \in \tau_1, x_{jt}^+ - x_{jt}^- \leq s_{j,t}^{max,+} - p_{j,t} + z_{j,t} \tag{53}$$

$$\forall t \in \tau_4, x_{jt}^+ - x_{jt}^- - Y_{j,t} \leq s_{j,t}^{max,+} - p_{j,t} + z_{j,t} \tag{54}$$

$$\forall t \in \tau_5, x_{jt}^+ - x_{jt}^- - Y_{j,t} + Y_{j,t-1} \leq \alpha_{j,t}^+ - p_{j,t} + z_{j,t} \tag{55}$$

Constraints (36) and (37) remain unchanged.

In summary, we have replaced system {(29)-(33), (35)-(38)} defining $\mathscr{P}_j$ by system {(36),(37), (44)-(55)}. The remaining variables in this new system are: $x_{j,t}^+$, $x_{j,t}^-$, and $Y_{j,t}$. Recall that we aim to compute an equivalent system with only the $x_{j,t}^+$ and $x_{j,t}^-$ remaining. We then eliminate successively the $Y_{j,t}$ variables using the Fourier-Motzkin elimination method (see for instance [133, pp.155-157]). The equivalent system of inequalities obtained defines the projected polytope $\hat{\mathscr{P}}_j$ for any prosumer $j \in J$.

Note that the Fourier-Motzkin elimination method is not polynomial and can be quite time-consuming for problems in many variables. This motivated the formulation that we proposed in Section 3.2.4 to model flexible consumption requirements using only T decision variables at most. In practice, the computational capabilities available may require to limit $|\tau_{j,2}|$, the number of time intervals during which flexible consumption can be scheduled.

We formulate the projected prosumer problem as follows:

$$(\hat{\text{P}}\text{-j}) \qquad \begin{array}{ll} \textbf{minimize} & \hat{c}_j \hat{x}_j \\ \textbf{subject to} & \hat{A}_j \hat{x}_j \leq \hat{b}_j, \hat{x}_j \geq 0 \end{array}$$

with $\hat{\mathscr{P}}_j = \{\hat{x}_j \in \mathbb{R}^{2T} : \hat{A}_j \hat{x}_j \leq \hat{b}_j\}$.

Finally, we denote by $\hat{\mathscr{C}}$ the set of acceptable cost vectors in the lower dimensional space:

$$\hat{\mathscr{C}} \triangleq \{\hat{c}_j \in \mathbb{R}^{2T} | (\hat{c}_j, 0_{(m-2T)}) \in \mathscr{C}\}$$

3.5.5 Selecting an initial cost vector in $\hat{\mathscr{C}}$

As a first step, we are looking for a cost vector $\hat{c}_j^{\bullet} \in \hat{\mathscr{C}}$ and a feasible schedule $\hat{x}_j^{\bullet} \in \hat{\mathscr{P}}_j$ as close as possible to $\hat{x}_j^{\star}$, which get close to meet the optimality conditions.

Observe that $\hat{x}_j^0 \in argmin_{\hat{x}_j}\{\hat{c}_j^{0\intercal}\hat{x}_j : \hat{A}_j\hat{x}_j \leq \hat{b}_j, \hat{x}_j \geq 0\}$ if and only if there exist $\gamma_j^0 \in \mathbb{R}^{2T}$ such that: (i) $\hat{A}_j\hat{x}_j^0 \leq \hat{b}_j, \hat{x}_j^0 \geq 0$ (primal feasibility), (ii) $\hat{A}_j^\intercal\gamma_j^0 \leq \hat{c}_j^0, \gamma_j^0 \leq 0$ (dual feasibility), and (iii) $\hat{c}_j^{0\intercal}\hat{x}_j^0 = \hat{b}_j^\intercal\gamma_j^0$ (strong duality).

Ideally, we would like to find a cost vector in $\hat{\mathscr{C}}$ that meets the optimality conditions above for a projected schedule as close as possible to $\hat{x}_j^{\star}$. Since we always have $\hat{c}_j^{0\intercal}\hat{x}_j^0 \geq \hat{b}_j^\intercal\gamma_j^0$ if $\hat{c}_j^0$ is feasible for the primal and $\hat{x}_j^0$ is feasible for the dual, we replace (iii) by $\hat{c}_j^{0\intercal}\hat{x}_j^0 \leq \rho \cdot \hat{b}_j^\intercal\gamma_j^0$ to improve feasibility, and try to keep $\rho \geq 1$ as close as possible to 1.

Define the following program:

$$
(\hat{\text{H}}\text{-j}) \qquad
\begin{array}{lll}
\textbf{minimize} & \|\hat{x}_j - \hat{x}_j^{\star}\| & \\
\textbf{subject to} & \hat{A}_j\hat{x}_j \leq \hat{b}_j, \hat{x}_j \geq 0 & \text{(primal)} \\
 & \hat{A}_j^\intercal\gamma_j \leq \hat{c}_j^0, \gamma_j \leq 0 & \text{(dual)} \\
 & \hat{c}_j^\intercal\hat{x}_j^{\star} \leq \rho \cdot \hat{b}_j^\intercal\gamma_j & \text{(duality condition)} \\
 & \hat{c}_j \in \hat{\mathscr{C}} &
\end{array}
$$

We try to solve (Ĥ-j) for $(\hat{x}_j, \hat{c}_j, \gamma_j)$ with $\rho = 1$, and if infeasible, increase ρ by a small ε until (Ĥ-j) becomes feasible. Denote by $(\hat{x}_j^{\bullet}, \hat{c}_j^{\bullet}, \gamma_j^{\bullet})$ the optimal solution obtained.

3.5.6 Finding a proxy extreme point in $\hat{\mathscr{P}}_j$

We now use $\hat{c}_j^{\bullet}$ to guide the search for a proxy extreme point $\hat{x}_j^{\star\!\!\!\circ}$ close to $\hat{x}_j^{\star}$. We solve (P̂-j) with $\hat{c}_j^{\bullet}$ as the cost vector, and denote by $\hat{x}_j^{\circ}$ the solution returned. All standard LP software returns an extreme point solution, either by using the simplex algorithm or by performing a crossover after termination of an interior point algorithm.

3.5.7 Ensuring unique $\hat{\mathscr{C}}$-exposability in $\hat{\mathscr{P}}_j$

By definition of $\hat{x}_j^\circ$, $\hat{c}_j^\bullet \in \hat{\mathscr{C}}$ exposes $\hat{x}_j^\circ$, but does not necessarily *uniquely* exposes $\hat{x}_j^\circ$. We are looking for a $\hat{c}_j^\circ \in \hat{\mathscr{C}}$ that uniquely exposes $\hat{x}_j^\circ$ for (P̂-j) in the strong sense.

Theorem 1. *$\hat{c}_j^0 \in \hat{\mathscr{C}}$ uniquely exposes $\hat{x}_j^0 \in \hat{\mathscr{P}}_j$ in the strong sense if and only if $\hat{x}_j^0$ is an extreme point of $\hat{\mathscr{P}}_j$ and $\hat{c}_j^0$ can be expressed as a strictly positive sum of all binding contraints at $\hat{x}_j^0$.*

Proof. We prove the theorem for the general case of a vector c that uniquely exposes a point v in polyhedron $P \subset \mathbb{R}^n$.

($\Leftarrow$) Let $Bx \geq b$ be the set of constraints that define P and are binding at v. By assumption, $Bv = b$ and $c = \pi^T B$ for a vector $\pi > 0$. Since v is an extreme point of P, v is a basic feasible solution and hence B contains n linearly independent rows. Therefore v is the unique solution to $Bv = b$. Let $w \in P$ and suppose $\pi^T Bw \equiv c \cdot w \leq c \cdot v \equiv \pi^T Bv \equiv \pi^T b$. Apply $\pi > 0$ to $Bw \geq b$ to get $\pi^T Bw = c \cdot w \geq \pi^T b$. Then $c \cdot w = c \cdot v$. If row i of B, denoted $B_{i\cdot}$, were such that $B_{i\cdot} w > b_i$, then since $\pi_i > 0$ we would have $\pi^T Bw > \pi^T b$, a contradiction. Therefore $Bw = b$ which implies $Bv = b$. Hence c uniquely exposes v in the strong sense.

($\Rightarrow$) If c uniquely exposes v but is not an extreme point, then $v = \lambda p + (1 - \lambda) q$ for $0 < \lambda < 1$, $p \in P, q \in P, p \neq q$ and $c \cdot v < c \cdot p$ and $c \cdot v < c \cdot q$. This contradicts $c \cdot v = \lambda c \cdot p + (1 - \lambda) c \cdot q$. Therefore v is an extreme point. We now must show that $c = \pi^T B$ for some vector $\pi > 0$ where B, b are as defined in the first part of the proof. By contradiction , suppose no such $\pi > 0$ exists. This means that the system

$$\alpha c = \pi^T B; \pi \geq \mathbf{1}; \alpha \geq 0, \pi \geq 0$$

has no solution. By Farkas's Lemma, there exist vectors y, w such that $w \geq 0, w \neq 0, w \leq By$, and $c \cdot y \leq 0$. Hence $By \geq 0$ and $y \neq 0$. For sufficienty small $\epsilon > 0$, the only constraints that define P which $v + \epsilon y$ could violate are those at which v is binding. For some such $\epsilon > 0$, let $v' = v + \epsilon y$. Then $Bv' = Bv + \epsilon By \geq Bv \geq b$, so $v' \in P$. Also, $c \cdot v' = c \cdot v + \epsilon c \cdot y \leq c \cdot v$. Since c uniquely exposes v, it must be that $v = v'$. But this contradicts $y \neq 0$. completing the proof. $\square$

By theorem 1, we therefore select $\hat{c}_j^\circ \in \hat{\mathscr{C}}$ that can be expressed as a strictly positive sum of all binding contraints at $\hat{x}_j^\circ$.

3.5.8 Returning to $\mathscr{P}_j$, the higher dimensional space

Theorem 2. *If $\hat{c}_j^\circ \in \hat{\mathscr{C}}$ uniquely exposes $\hat{x}_j^\circ$ in the strong sense, $c_j^\circ = (\hat{c}_j^\circ, 0, ..., 0) \in \mathscr{C}$ uniquely exposes x_j° in the weak sense.*

Proof. First, filling out the vector $\hat{c}_j^\circ \in \hat{\mathscr{C}}$ with zeros makes the resulting vector c_j° an element of $\mathscr{C}$, because having those terms equal to 0 is precisely the additional condition that must be satisfied for membership in $\mathscr{C}$. Second, for the main part of the proof, let x_j^1 be an optimal solution to the problem of minimizing $c_j^\circ \cdot x$ on the higher dimensional polytope $\mathscr{P}_j$. Following the definition of exposure in the weak sense, we must prove that $\hat{x}_j^1 = \hat{x}_j^\circ$. By construction, for any (higher-dimensional) point x_j, $c_j^\circ \cdot x_j = \hat{c}_j^\circ \cdot \hat{x}_j$. By optimality of x_j^1, it follows that

$$\forall x_j \in \mathscr{P}_j \quad \hat{c}_j^\circ \cdot \hat{x}_j = c_j^\circ \cdot x_j \leq c_j^\circ \cdot x_j^1 = \hat{c}_j^\circ \cdot \hat{x}_j^1.$$

On the other hand, $\hat{x}_j^\circ$ is the unique minimizer of the objective vector $\hat{c}_j^\circ$ on the projected polyhedron. Therefore, $\hat{x}_j^1 = \hat{x}_j^\circ$, proving the theorem. $\square$

We denote by $x_j^\star \in \mathscr{P}_j$ the extreme point uniquely exposed by c_j° in the weak sense. By definition of c_j° we have $\hat{x}_j^\star = \hat{x}_j^\circ$.

3.5.9 Final power schedules for grid-controlled assets

We solve the master problem again, but assuming that each end-user effectively adopts the power schedules $x_j^\star$ that were uniquely $\mathscr{C}$-exposed, and select power schedules for grid-controlled assets accordingly:

$$\text{(MP-f)} \qquad \begin{aligned} &\textbf{minimize} && \Phi_{\mathcal{A}} = \sum_{i \in I} \sum_{t=1}^{T} C_{i,t} \\ &\textbf{subject to} && Ax \leq b, x \geq 0 \\ & && \forall j \in J, x_j = x_j^{\star} \end{aligned}$$

Let $\Phi_{\mathcal{A}}^{\star}$ be the optimum obtained when solving (MP-f). We know that $\Phi_{\mathcal{A}}^{\star}$ can be induced, and hopefully $\Phi_{\mathcal{A}}^{\star}$ is close to $\Phi_{\mathcal{A}}^{\bigstar}$, the team optimum.

3.6 Post-processing: addressing fairness

In this section, we transform c_j° into $c_j^{\star} \in \mathscr{C}$, the "fair" price that uniquely exposes $x_j^{\star}$ in the weak sense.

3.6.1 Perceived fairness

In the context of dynamic pricing, *fairness* is a judgement of whether a price offered (outcome), and/or the rationale for offering a certain price (process), are reasonable, acceptable, or justifiable. *Price* fairness draws on equity theory and distributive justice, while *pricing* fairness relates to procedural justice.

Fairness assessments are inherently subjective and usually studied from the buyer's perspective: price fairness involves comparing (explicitly or implicitly) one price with another reference price, or with a range of reference prices; pricing fairness involves the comparison of a pricing process to social norms [166].

Notions of *fairness* and *unfairness* are related, although fairness can be more difficult to articulate; unfairness is typically clearer and more concrete –people "know" what is unfair when they see it or experience it. The practice of yield management in the hospitality and airline industries shows that, although buyers' perceptions of price unfairness are based on perceived price differences, a fair pricing scheme does not necessarily imply a one-price policy for everyone, nor does it mean that customers do not accept price changes or price differences.

3.6.2 Axiomatic characterization

We propose that an electricity pricing scheme that verifies the following set of axioms can be considered as fair, or at least will *not* be considered as unfair by residential end-users:

Axiom 1. *If users j_1 and j_2 make the same marginal contributions to minimize the total generation costs over $\mathcal{T}$, then the payments requested from j_1 and j_2 over $\mathcal{T}$ should be equal.*

Axiom 2. *Assume users j_1 and j_2 are identical in every way, except for their fixed consumption requirements. If the fixed requirements of j_1 are smaller than the fixed requirement of j_2 for every time period $t \in \mathcal{T}$, then j_1 should* not *be charged more than j_2 over $\mathcal{T}$.*

Axiom 3. *Assume users j_1 and j_2 are identical in every way, except for their flexible consumption requirements.*

(a) If j_1 is more flexible than j_2 (i.e. if j_1 asks for the same *amounts over $\mathcal{T}$, but over* wider *time intervals), then j_1 should* not *be charged more than j_2 over $\mathcal{T}$.*

(b) If j_1 asks for smaller *amounts than j_{t_2} over the* same *time intervals, then j_1 should* not *be charged more than j_2 over $\mathcal{T}$.*

Axiom 4. *Assume users j_1 and j_2 are identical in every way, except for their storage systems. If j_1's storage system is faster and/or has a larger capacity than j_2's storage system for every time period $t \in \mathcal{T}$, then j_1 should* not *be charged more than j_2 over $\mathcal{T}$.*

Axiom 5. *Assume users j_1 and j_2 are identical in every way, except for their distributed generation capabilities. If j_1 produces at least as much as j_2 for every time period $t \in \mathcal{T}$, then j_1 should* not *be charged more than j_2 over $\mathcal{T}$.*

3.6.3 Computing the fair price

The total payments requested from end-users over $\mathcal{T}$ should be equal to the total generation costs incurred to the provider over $\mathcal{T}$ (feasibility requirement). Let $\Psi_j^{\star}$ be the total charge that end-user j ends up paying over $\mathcal{T}$ after receiving a pricing scheme that uniquely exposes $x_j^{\star}$ in the weak sense. We must have:

$$\sum_{j \in J} \Psi_j^{\star} = \Phi_{\mathcal{A}}^{\star} \tag{56}$$

Let $\Phi_{\mathcal{A}}^{\star}$ be the team optimum obtained when solving (MP). For any $j_0 \in J$, let $\Phi_{-j_0}^{\star}$ be the optimum obtained when solving (MP) for the set of end-users $J \backslash \{j_0\}$ instead of J. Denote by $\Delta_{j_0}(J) \triangleq \Phi_{\mathcal{A}}^{\star} - \Phi_{-j_0}^{\star}$ the marginal contribution of end-user j_0 in the energy game where all end-users in J work cooperatively with the provider to minimize the provider's generation costs. Axiom 1 requires that, for any j_1 and j_2 in J, we have:

$$\frac{\Psi_{j_1}^{\star}}{\Phi_{\mathcal{A}}^{\star} - \Phi_{-j_1}^{\star}} = \frac{\Psi_{j_2}^{\star}}{\Phi_{\mathcal{A}}^{\star} - \Phi_{-j_2}^{\star}} \tag{57}$$

From (57), we obtain:

$$\sum_{j_2 \in J} \Psi_{j_2}^{\star} = \frac{\Psi_{j_1}^{\star}}{\Phi_{\mathcal{A}}^{\star} - \Phi_{-j_1}^{\star}} \sum_{j_2 \in J} (\Phi_{\mathcal{A}}^{\star} - \Phi_{-j_2}^{\star}) \tag{58}$$

and combining with (56):

$$\Psi_{j_1}^{\star} = \frac{\Phi_{\mathcal{A}}^{\star} - \Phi_{-j_1}^{\star}}{\sum_{j_2 \in J} (\Phi_{\mathcal{A}}^{\star} - \Phi_{-j_2}^{\star})} \Phi_{\mathcal{A}}^{\star} \tag{59}$$

The optima $\Phi_{\mathcal{A}}^{\star}$ and $\Phi_{\mathcal{A}}^{\star}$ are known already. However, computing $\Phi_{-j}^{\star}$ centrally for each $j \in J$ requires to solve problem (MP) $|J|$ times, which can be computationally expensive.

We propose an alternative approach to compute an approximation of $\Phi^\star_{-j}$ in a distributed manner, following the multi-level decomposition introduced in Section 3.4. For any level-1 super-prosumer x, let $\Phi^\star_{-x}$ be the optimum obtained when solving (MP) for the set of level-1 super-prosumers excluding super-prosumer x. Each level-1 super-prosumer x subsequently determines an approximation of $\Phi^\star_{-j_0}$ for each of its constituting level-2 (super-)prosumer $j_0 \in J_{\mathrm{x}}$ by solving the following program:

$$\text{(PHI-x-}j_0\text{)} \qquad \begin{array}{lll} \textbf{minimize} & \tilde{\Phi}_{-j_0} = \omega_x \sum_{i\in I} \sum_{t=1}^{T} C_{i,t} & \\ \textbf{subject to} & A_j x_j \leq b_j & \forall j \in J_{\mathrm{x}} \backslash \{j_0\} \end{array}$$

where $\omega_x \triangleq \frac{\hat{x}^\star_{\mathrm{x}}}{\sum_{\mathrm{x}\in J^\uparrow_{\mathrm{x}}} \hat{x}^\star_{\mathrm{x}}}$, and $J^\uparrow_{\mathrm{x}}$ is the set of super-prosumers that includes x, and forms a larger super-prosumer at the immediate upper level (except at level 1, where all level-1 super-prosumers are in $J^\uparrow_{\mathrm{x}}$). This process iterates until $\tilde{\Phi}^\star_{-j}$ has been computed for each residential prosumer $j \in J$. Substituting $\Phi^\star_{-j}$ for $\tilde{\Phi}^\star_{-j}$ in (59), we can compute $\Psi^\star_j$ for all j in J.

Theorem 3. *For any end-user $j \in J$, $\Psi^\star_j$ as defined in* {(56)-(57)} *verifies Axioms 1 to 5.*

Proof. First, note that $\Psi^\star_j$ verifies Axiom 1 by definition. For each of the Axioms 2 to 5 to be verified, we must have $\Psi^\star_{j_1} \leq \Psi^\star_{j_2}$, which is equivalent to $\Phi^\star_{\mathcal{A}} - \Phi^\star_{-j_1} \leq \Phi^\star_{\mathcal{A}} - \Phi^\star_{-j_2}$ according to (57), or $\Phi^\star_{-j_2} \leq \Phi^\star_{-j_1}$. Let $\mathscr{P}_{-j}$ be the polytope for (MP) corresponding to the case where the set of end-users considered is $J\backslash\{j\}$ (the sets I and L and the constraints on the generation and grid storage remain unchanged). Evidently, if $\mathscr{P}_{-j_1} \subseteq \mathscr{P}_{-j_2}$, then $\Phi^\star_{-j_2} \leq \Phi^\star_{-j_1}$.

We show that $\mathscr{P}_{-j_1} \subseteq \mathscr{P}_{-j_2}$ is true for each axiom:

Axiom 2: redefine $z_{j,t}$ as a variable in the end-user optimization problem, with the additional constraints $z_{j,t} \geq \bar{z}_{j,t}$, where $\bar{z}_{j,t}$ is the fixed consumption during t (former value of $z_{j,t}$ when modeled as a parameter). At optimality $z_{j,t}$ will always be equal to

$\bar{z}_{j,t}$ since end-user j is minimizing its energy costs. Since $\bar{z}_{j,t_1} \leq \bar{z}_{j,t_2}$, $\mathscr{P}_{-j_1} \subseteq \mathscr{P}_{-j_2}$ is true.

Axiom 3.a: $\forall (t_1, t_2) \in \mathcal{T}^2$ s.t. $t_1 < t_2$ and $E_{j_1,t_1,t_2} > 0$, $\exists (t_3, t_4) \in \mathcal{T}^2$ s.t. $t_1 \leq t_3 < t_4 \leq t_2$ and $E_{j_1,t_1,t_2} = E_{j_2,t_3,t_4}$. Therefore $\forall (t_1, t_2) \in \mathcal{T}^2$ s.t. $t_1 < t_2, \Gamma_{j_1,t_1,t_2} \leq \Gamma_{j_2,t_1,t_2}$, and $\chi'_{j_2} \subseteq \chi'_{j_1}$, which means $\mathscr{P}_{-j_1} \subseteq \mathscr{P}_{-j_2}$ is true.

Axiom 3.b: $\forall (t_1, t_2) \in \mathcal{T}^2$ s.t. $t_1 < t_2, E_{j_1,t_1,t_2} \leq E_{j_2,t_1,t_2}$. Therefore $\chi'_{j_2} \subseteq \chi'_{j_1}$, and $\mathscr{P}_{-j_1} \subseteq \mathscr{P}_{-j_2}$ is true.

Axiom 4: $\forall t \in \mathcal{T}$, $s^{max}_{j_1,t} \geq s^{max}_{j_2,t}, s^{min}_{j_1,t} \geq s^{min}_{j_2,t}, s^{max,+}_{j_1,t} \geq s^{max,+}_{j_2,t}$, and $s^{max,-}_{j_1,t} \geq s^{max,-}_{j_2,t}$. Therefore $\mathscr{P}_{-j_1} \subseteq \mathscr{P}_{-j_2}$ is true.

Axiom 5: redefine $p_{j,t}$ as a variable and add constraints $0 \leq p_{j,t} \leq \bar{p}_{j,t}$, where $\bar{p}_{j,t}$ is the expected local generation during t (former value of $p_{j,t}$ when modeled as a parameter). At optimality $p_{j,t}$ will always be equal to $\bar{p}_{j,t}$ since j is minimizing costs, and $p_{j,t}$ is essentially a free energy source. Since $\bar{p}_{j,t_1} \geq \bar{p}_{j,t_2}$, $\mathscr{P}_{-j_1} \subseteq \mathscr{P}_{-j_2}$ is true. $\square$

In practice, when selecting $\hat{c}^{\circ}_j$ as explained in section 3.5.7, we also require that $\hat{c}^{\circ}_j \cdot \hat{x}^{\circ}_j$ be as close as possible to $\Psi^{\star}_j$ by finding a $\delta \geq 0$ as small as possible such that $\Psi^{\star}_j(1-\delta) \leq \hat{c}^{\circ}_j \cdot \hat{x}^{\circ}_j \leq \Psi^{\star}_j(1+\delta)$ if $\delta < 1$, and $0 < \hat{c}^{\circ}_j \cdot \hat{x}^{\circ}_j \leq \Psi^{\star}_j(1+\delta)$ else. $\Psi^{\star}_j$ is computed as explained above. When the δ selected is strictly positive, $\hat{c}^{\circ}_j$ is rescaled such that $\hat{c}^{\circ}_j \cdot \hat{x}^{\circ}_j$ be equal to $\Psi^{\star}_j$. We denote by $c^{\star}_j$ the final price vector obtained.

3.7 Numerical simulations

In this section, we present simulation results for two real-data test cases that demonstrate the proposed pricing algorithm.

3.7.1 Building the test cases

To the best of our knowledge, there does not exist any standard, publicly-available case involving a large number of residential prosumers at the time of writing. For this reason, we begin by building two test cases using historical data from *Dataport*,

Table 3.3: Definition of agent types and characteristics of the Winter and Summer cases

		Energy functions				Winter case			Summer case		
	Agent type	Fixed consumption	Fixed generation	Flexible consumption	EV storage	# of agents	% of agents		# of agents	% of agents	
Not flexible	I	*				141[a]	26.8%	47.0%	181	31.8%	52.4%
	II	*	*			106	20.2%		117	20.6%	
Flexible	III	*		*		165	31.4%	53.0%	176	30.9%	47.6%
	IV	*			*	7	1.3%		4	0.7%	
	V	*	*	*		61	11.6%		39	6.9%	
	VI	*	*		*	13	2.5%		20	3.5%	
	VII	*		*	*	8	1.5%		6	1.1%	
	VIII	*	*	*	*	25	4.8%		26	4.6%	
Winter case	#	526	205	259[b]	53						
	%	100.0%	39.0%	49.2%	10.1%						
Summer case	#	569	202	247	56						
	%	100.0%	35.5%	43.4%	9.8%						

[a] "In the Winter case, 141 agents are of type I"
[b] "In the Winter case, 259 agents have flexible consumption capabilities"

a database of disaggregated customer energy data maintained by Pecan Street Inc. and available to university researchers.

The time series displayed in *Dataport* correponds to real-time measurements made at residential homes, most of them located in Austin, TX. These homes are instrumented to record the individual consumption of electric loads and appliances as well as the solar generation and electric vehicle charging cycle when available.

The first case, which we refer to as the *Summer* case, consists of $|J| = 569$ residential homes. The Summer case is based on historical data for the period of time starting at 6:00 on 6/20/2014 and ending at 6:00 on 6/21/2014. The second case, which we refer to as the *Winter* case, consists of $|J| = 526$ residential homes. The Winter case is based on historical data for the period of time starting at 6:00 on 12/20/2014 and ending at 6:00 on 12/21/2014. For both cases, we included all the available observations in *Dataport* for the period of time considered after removing the homes with missing or inconsistent measurements.

The generic end-user model previously introduced encompasses several energy functions: non-controllable generation, fixed and flexible consumption, and storage (Table 3.2). However, only a subset of these functions may be *effectively* available to the end-user. This leads us to define eight different agent types, each type corresponding to a certain combination of energy functions. Types I and II correspond to agents that are not flexible, while types III to VIII have some degrees of flexibility. Table 3.3 maps the agent types to the energy functions effectively available. Table 3.3 also presents the distribution of agents per type and per energy function for the Winter and Summer cases.

For simplicity, and without loss of generality, grid storage is not considered in this section. Grid generation is also limited to one controllable unit given the relatively small size of the system.

3.7.2 Setting realistic values for the model parameters

The *Dataport* time series define a baseline scenario for each of the two test cases. Each baseline scenario assumes flat-rate electricity pricing. In addition, we set the model parameters introduced in section 3.2 to realistic values consistent with the baseline scenarios. We now explain in detail how these values are set.

3.7.2.1 Flexible consumption

Four types of flexible loads are considered in this simulation section: clothes washer, dishwasher, dryer, and water heater. For every agent j with flexible consumption capabilities, we limit the number of flexible time intervals to $|\tau_{j,2}| = 8$ to prevent memory overflow; we further assume consecutive time intervals without loss of generality ($\tau_{j,2} = \mathcal{F}_{j,1}$). Simulations are run on a 4-core, 6GB machine. Larger computational capabilities would likely allow for a higher $|\tau_{j,2}|$.

We use the following heuristic to allocate the flexible time intervals. The $T = 24$ time intervals are partitioned into four blocks: 6:00-8:00; 8:00-14:00; 14:00-18:00; 18:00-6:00. Assuming that the provider is looking to smooth the aggregated demand over $\mathcal{T} = \{1, ..., 24\}$, we first examine, for each end-user j, if any flexible loads start after 18:00 under the baseline scenario, which is also the block with the highest aggregated demand. If no flexible loads are scheduled after 18:00, the 8:00-14:00 block is examined, followed by the 14:00-18:00 block, and finally the 6:00-8:00 block.

Once a block has been selected for each end-user j, we examine the flexible loads scheduled within that block under the baseline scenario. The beginning of time interval t_1 where the first flexible load a_1 starts defines the beginning of the flexible time period $\tau_{j,2}$. This flexible period $\tau_{j,2}$ terminates 8 time intervals later, or at the end of time period 24 (6:00), whichever comes first. We denote by t_2 the end of $\tau_{j,2}$. The parameter E_{j,t_1,t_2} is set to the amount of energy used by a_1 under the baseline scenario while $E^{max}_{j,t_1,t_2,t}$ is set to the maximum consumption rate observed in the baseline scenario for load a_1.

Particular situations are handled as follows. When multiple flexible loads start at t_2, there are all aggregated together into E_{j,t_1,t_2} and $E^{max}_{j,t_1,t_2,t}$. For any additional flexible load starting during interval t'_1 with $t_1 < t'_1 < t_2$, the parameters E_{j,t'_1,t_2} and E^{max}_{j,t'_1,t_2} are set accordingly. For flexible loads starting before t_2 but ending after t_2 under the baseline scenario, only the fraction of energy consumed before t_2 is considered flexible. Flexible loads scheduled oustide of $\tau_{j,2}$ are treated as fixed loads.

3.7.2.2 Fixed consumption and local generation

For each end-user j, the fixed power requirements z_j and the energy produced locally p_j are set according to the baseline scenario since those two quantities are assumed to be non-controllable.

3.7.2.3 Electric-vehicle storage

The only storage capabilities recorded in *Dataport* consist of electric-vehicle batteries. In the following, we assume that any vehicle connected at the beginning of the day (6:00) under the baseline scenario can be used to smooth the demand until 8:00, provided that it is left fully charged at 8:00. We also assume that any electric vehicle arriving sometime during the 18:00-6:00 block can be used to smooth the demand as long as the batteries are fully charged by 6:00.

The maximum charging rate assigned to each vehicle corresponds to the maximum charging rate observed in the baseline scenario. We assume that vehicle-to-grid operations are enabled, and that charging and discharging rates are equal for a given vehicle. The initial storage levels when the vehicle connects to the home grid are set according to the initial levels observed in the baseline scenario.

3.7.3 Simulation results assuming perfect information

Table 3.4 presents a summary of the results obtained for the Winter and Summer cases. Define $\Phi^0_{\mathcal{A}}$ the cumulative generation cost over $\mathcal{T}$ for the baseline scenario. For both the Winter and Summer cases, we observe that $\Phi^0_{\mathcal{A}} \geq \Phi^{\star}_{\mathcal{A}} \geq \Phi^{\star}_{\mathcal{A}}$. The costs obtained are naturally dependent on the cost-curve of the generation unit.

Most importantly, the proposed pricing algorithm induces in both cases an aggregated schedule $\sum_{j \in J} \Delta x^{\star}_j$ that remains within 2% of the desired aggregated schedule $\sum_{j \in J} \Delta x^{\star}_j$.

Figure 3.6 shows the baseline, desired, and induced schedules aggregated across the *flexible* agents only (types III to VIII), as well as the error between the desired and induced schedules over $\mathcal{T}$. Figure 3.7 shows the same quantities aggregated across all the agents, flexible and non-flexible. The proposed pricing algorithm allows to reduce the consumption peak by 13% in the Winter case, and 18% in the Summer case compared to the baseline (or reference) scenarios.

Tables 3.5 and 3.6 present the performance of the proposed pricing algorithm per flexible agent type. For both test cases, the average runtime to compute $\hat{\mathscr{P}}_j$ remains below 5 seconds. We first try to solve ($\hat{\text{H}}$-j) with $\rho = 0$, and increase ρ by $\varepsilon = 1\%$ every 90 seconds if the attempt is unsuccessful. For the vast majority of agents, ($\hat{\text{H}}$-j) is solved with $\rho = 0$, the remaining agents solving with $\rho = 0.01$. The average combined runtime across all flexible agents is below 17 seconds in both test cases. Results per agent type show that the average combined runtime increases by a factor 2 to 3 when both flexible consumption and storage are available (agent types VII and VIII).

Table 3.7 presents the proportion of agents for which the desired schedule $x^{\star}_j$ (or its projection $\hat{x}^{\star}_j$) is an extreme point of $\mathscr{P}_j$ (resp. $\hat{\mathscr{P}}_j$). While a majority of desired schedule $x^{\star}_j$ are extreme points for $\mathscr{P}_j$, none of the projected schedules are found to be extreme points for $\hat{\mathscr{P}}_j$. Most importantly, none of the desired schedules are uniquely

Table 3.4: System demand and generation cost

	System demand (MW)	Generation cost ($)			Aggr. error (%)
		$\Phi^0_{\mathcal{A}}$	$\Phi^\star_{\mathcal{A}}$	$\Phi^\star_{\mathcal{A}}$	$\frac{\lVert\sum_j \Delta x^\star_j - \sum_j \Delta x^\star_j\rVert}{\lVert\sum_j \Delta x^\star_j\rVert}$
Winter case	12.31	2,870	1,231	1,290	1.76
Summer case	14.99	16,745	10,414	10,414	0.71

$\mathscr{C}$-exposable for (P-j) in either the strong sense, or even the weak sense. This result serves as ex-post justification for the algorithmic approach proposed in section 3.5.

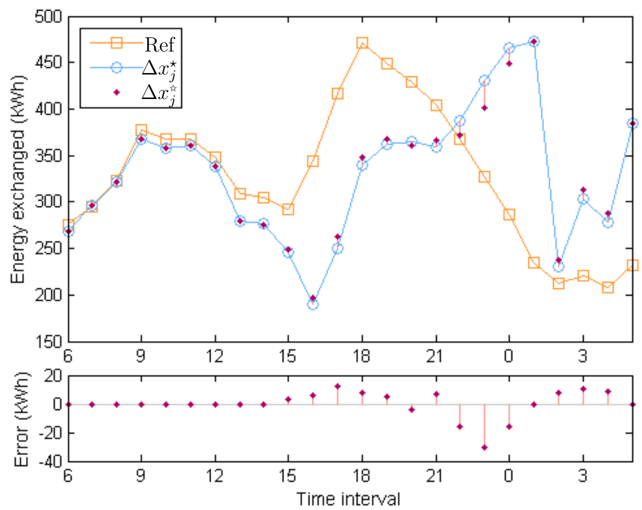
3.7.4 Simulation results assuming imperfect information

The simulation results presented above assume an ideal situation where the provider has full knowledge of the end-users optimization problems. We now study the sensitivity of the results to this assumption.

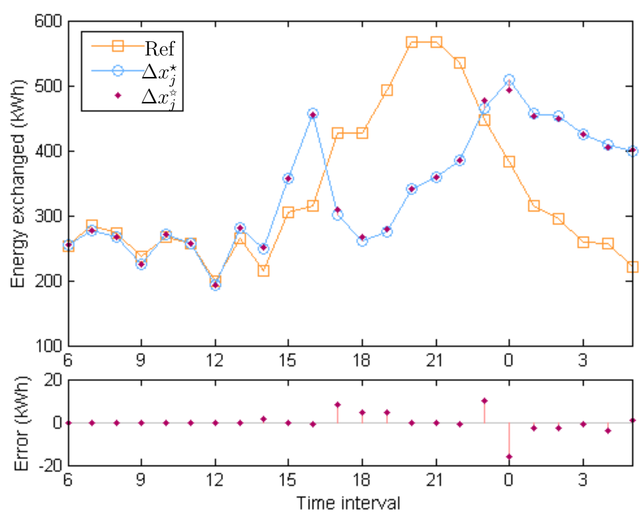
The information describing the end-users problems can be classified into two types, *structural* and *usage*. The structural information refers to parameters that are typically fixed (PCC limits, charging/discharging rates, etc.), while the usage information refers to parameters characterizing the end-user energy behavior in terms of *time* (when?) and *magnitude* (how much?).

In the following, we focus our sensitivity analysis on the effect of uncertainty over *magnitude*. Four types of parameters are of particular interest: the fixed consumption requirements ($z_{j,t}$), the flexible consumption requirements (E_{j,t_1,t_2}), the solar energy generated ($p_{j,t}$), and the initial battery level at the time when the electric car connects to the home grid (modeled as a one-time energy spike in equation (33)).

We now model these parameters as random variables to account for uncertainty. For each variable X, the parameter value assumed in the previous simulations is now treated as the *expected* value $\bar{X}$ of X. We further assume that X follows a continuous uniform distribution on the interval $(\bar{X}-\lambda, \bar{X}+\lambda)$ where λ depends on the simulation

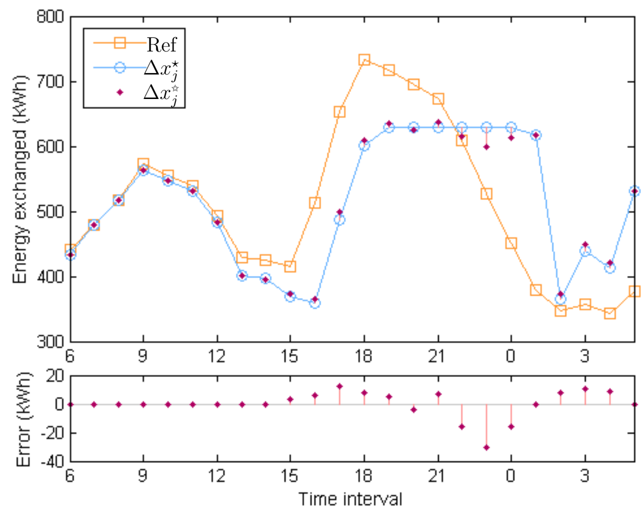


(a) Winter case.

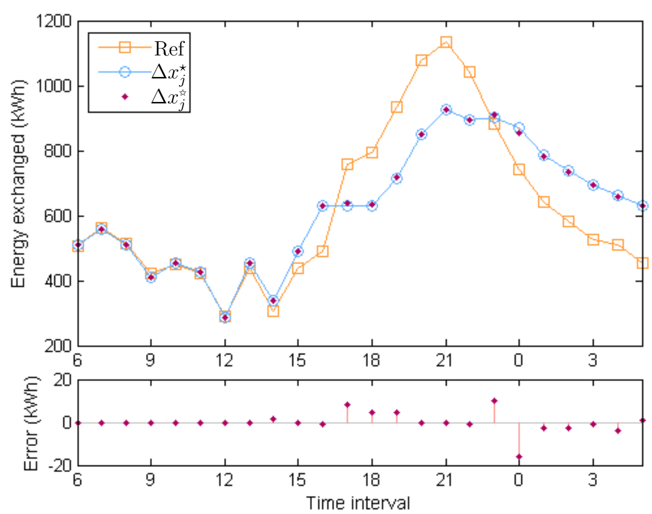


(b) Summer case.

Figure 3.6: Demand aggregated across *flexible* agents *only*.



(a) Winter case.



(b) Summer case.

Figure 3.7: Demand aggregated across *all* agent types.

Table 3.5: Performance of proposed method for the Winter case assuming perfect information

Agent type	Runtime to compute $\hat{\mathscr{P}}_j$ (s)				Runtime to solve (Ĥ-j) (s)				Combined runtime (s)				Final ρ value ($\varepsilon = 0.01$)		Indiv. error $\frac{\|\Delta x_j^\star - \Delta x_j^\circ\|}{\|\Delta x_j^\star\|}$ (%)			
	min	med	mea	max	min	med	mea	max	min	med	mea	max	mea	max	min	med	mea	max
III	0.09	3.25	5.07	20.11	0.10	4.57	10.38	77.24	0.19	7.81	15.45	97.35	0.00	0.00	0.00	0.00	0.01	1.91
IV	0.04	0.05	0.05	0.06	0.02	0.02	0.02	0.05	0.06	0.06	0.07	0.10	0.00	0.00	0.00	0.00	0.00	0.00
V	0.82	3.12	4.62	19.94	0.68	5.33	7.68	41.47	1.51	8.42	12.31	58.29	0.00	0.00	0.00	0.00	0.00	0.00
VI	0.04	0.05	0.05	0.06	0.02	0.02	0.02	0.03	0.06	0.07	0.07	0.08	0.00	0.00	0.00	0.00	0.00	0.00
VII	3.16	4.07	5.61	12.61	3.90	19.66	37.72	105.76	7.06	25.99	43.34	110.55	0.00	0.01	0.00	0.32	5.94	22.04
VIII	0.88	3.68	8.12	19.51	0.61	11.36	34.87	138.93	1.48	16.50	42.99	156.53	0.00	0.01	0.00	9.06	13.70	46.06
III-VIII	0.04	3.18	4.90	20.11	0.02	4.64	12.03	138.93	0.06	7.97	16.92	156.53	0.00	0.01	0.00	0.00	1.41	46.06

Table 3.6: Performance of proposed method for the Summer case assuming perfect information

Agent type	Runtime to compute $\hat{\mathscr{P}}_j$ (s)				Runtime to solve (Ĥ-j) (s)				Combined runtime (s)				Final ρ value ($\varepsilon = 0.01$)		Indiv. error $\frac{\lVert \Delta x_j^\star - \Delta x_j^\circ \rVert}{\lVert \Delta x_j^\star \rVert}$ (%)			
	min	med	mea	max	min	med	mea	max	min	med	mea	max	mea	max	min	med	mea	max
III	0.06	3.21	4.91	20.23	0.04	4.55	9.33	78.93	0.10	7.75	14.24	99.11	0.00	0.00	0.00	0.00	0.02	2.69
IV	0.04	0.05	0.05	0.05	0.02	0.02	0.02	0.02	0.06	0.06	0.06	0.07	0.00	0.00	0.00	0.00	0.00	0.00
V	0.06	3.23	4.67	19.34	0.05	4.55	9.37	52.13	0.11	7.93	14.04	65.90	0.00	0.00	0.00	0.00	0.00	0.00
VI	0.04	0.05	0.05	0.06	0.02	0.02	0.02	0.03	0.06	0.06	0.07	0.09	0.00	0.01	0.00	0.00	0.75	7.63
VII	2.96	3.18	4.25	9.79	5.16	6.09	34.10	132.23	8.12	9.30	38.35	142.02	0.00	0.01	0.00	0.00	2.47	14.81
VIII	0.22	3.33	7.75	19.41	0.26	5.85	20.60	119.84	0.47	9.07	28.35	139.25	0.00	0.01	0.00	1.41	5.81	22.78
III-VIII	0.04	3.20	4.70	20.23	0.02	4.51	10.14	132.23	0.06	7.71	14.85	142.02	0.00	0.01	0.00	0.00	0.68	22.78

Table 3.7: Exposability of $x_j^\star$ in $\mathscr{P}_j$, and $\hat{x}_j^\star$ in $\hat{\mathscr{P}}_j$, per type of flexible agent

Agent type	Winter Case				Summer Case			
	$x_j^\star$ extreme point (%)	$x_j^\star$ uniquely exposable (%)	$\hat{x}_j^\star$ extreme point (%)	$\hat{x}_j^\star$ uniquely exposable (%)	$x_j^\star$ extreme point (%)	$x_j^\star$ uniquely exposable (%)	$\hat{x}_j^\star$ extreme point (%)	$\hat{x}_j^\star$ uniquely exposable (%)
III	99.4[a]	0.0	0.0	0.0	99.4	0.0	0.0	0.0
IV	100.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0
V	100.0	0.0	0.0	0.0	85.0	0.0	0.0	0.0
VI	100.0	0.0	0.0	0.0	85.0	0.0	0.0	0.0
VII	87.5	0.0	0.0	0.0	100.0	0.0	0.0	0.0
VIII	84.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0
III-VIII	97.8	0.0	0.0	0.0	98.5	0.0	0.0	0.0

[a] "For 99.4% of the type-III agents, $x_j^\star$ is an extreme point of $\mathscr{P}_j$"

scenario.

We define four scenario categories: *cons*-λ, *gen*-λ, *stor*-λ and *all*-λ. In category *cons*-λ, only the fixed and flexible consumption requirements are modeled as random variables, with λ varying from 5% to 30%. In category *gen*-λ, only the energy generated locally is modeled as a random variable, with λ varying from 5% to 30%. Category *stor*-λ contains a single scenario where the initial battery levels are modeled as random variables and $\lambda = 5\%$. Finally, category *all*-λ also contains a unique scenario where the fixed and flexible consumption requirements, the energy generated locally and the initial battery levels are all modeled as random variables, and $\lambda = 5\%$. Parameter λ only takes one value when the initial battery levels are involved to avoid infeasibility (recall that the charging and discharing rates remain unchanged).

In the scenarios defined above, we solve (MP) and select the electricity prices $\pi_{j,t}$ assuming that the random variables take their expected values. For each end-user j, we then examine the end-user response $\tilde{x}_j^\star$ to these prices when the variables take their actual, random value.

Table 3.8 compares the simulation results obtained when assuming imperfect information to *perfect-info*, the scenario assuming perfect information. For both the Winter and Summer cases, we note an increase in the average individual error. However, the increase in the *aggregated* error remains small, with a maximum at 3.64% for scenario *cons-30* in the Winter case.

Table 3.9 and figure 3.8 show the impact of imperfect information on the provider revenues and individual end-user bills. Imperfect information leads to an average increase in the end-user bills of up to 86 cents (*cons-25*, winter), and a maximum increase observed across the simulation scenarios considered of \$27.99 (*cons-25*, summer). Imperfect information scenarios always lead to an increase in the provider revenues.

The results above show that, from the provider standpoint, the proposed pricing algorithm is robust with respect to uncertainty as imperfect information has a very limited impact on the aggregated error across the energy schedules induced, and does not incur financial losses. However, from the residential end-users standpoint, uncertainty leads to an increase in individual bills that may undermine fairness between the agents. These results could motivate future work investigating further the impact of imperfect information on more complex scenarios, including scenarios modeling uncertainty on magnitude *and* time.

3.8 Conclusions

This chapter proposes an electricity pricing scheme that induces autonomous residential prosumers to behave cooperatively and minimize the provider's generation costs.

We formulate an economic dispatch model that explicitly accounts for flexible consumption, storage, and generation capabilities downstream of the meter, as well as bidirectional power flows. We solve this enhanced economic dispatch in a distributed way and obtain the team optimum using multi-level primal decomposition to reduce the size of the problem, and increase end-user privacy protection. Although our focus in this chapter is on pricing, the enhanced economic dispatch model proposed could be used extensively in future work to assess the impact on the team optimum of various technology penetrations downstream of the meter (flexible appliances, solar generation, electric vehicles, etc.). Additional contraints such as network constraints could also be added to the model.

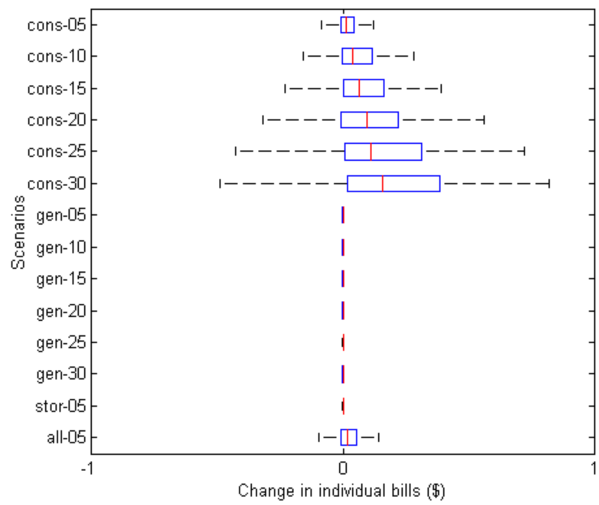
We propose a non-iterative pricing algorithm using convex programming and inverse linear programming that induces residential prosumers to autonomously achieve an optimum close to the team optimum. Different from existing non-iterative algorithms, our approach does not use backward induction and does not require closed-form expressions. The issue of fairness is addressed, taking into account the marginal

Table 3.8: Performance of proposed method under imperfect information, flexible agents only

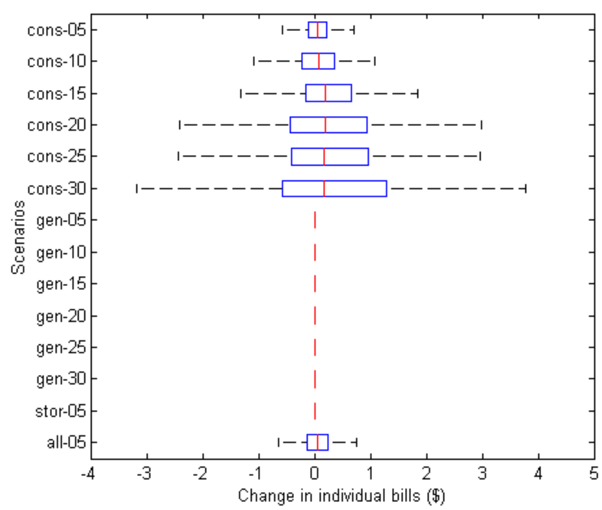
Scenario	Winter case					Summer case				
	Aggregated error	Individual error				Aggregated error	Individual error			
	$\frac{\|\sum_j x_j^\star - \sum_j \tilde{x}_j^\circ\|}{\|\sum_j x_j^\star\|}$ (%)	$\frac{\|x_j^\star - \tilde{x}_j^\circ\|}{\|x_j^\star\|}$ (%)				$\frac{\|\sum_j x_j^\star - \sum_j \tilde{x}_j^\circ\|}{\|\sum_j x_j^\star\|}$ (%)	$\frac{\|x_j^\star - \tilde{x}_j^\circ\|}{\|x_j^\star\|}$ (%)			
		min	med	mea	max		min	med	mea	max
perfect-info	2.71	0.00	0.00	1.41	46.06	1.32	0.00	0.00	0.68	22.78
cons-05	2.74	0.30	2.65	3.84	46.50	1.40	0.68	2.65	3.23	24.28
cons-10	2.71	0.82	5.27	6.24	46.60	1.52	1.54	5.23	5.77	27.57
cons-15	3.05	0.97	7.91	8.70	47.37	1.66	1.99	7.81	8.30	27.01
cons-20	3.10	1.33	10.65	11.05	47.26	2.06	2.90	10.81	11.10	31.57
cons-25	3.58	1.70	13.18	13.66	49.46	2.07	3.24	12.95	13.37	31.59
cons-30	3.64	1.99	15.93	16.06	49.59	2.99	3.86	15.47	15.92	37.45
gen-05	2.71	0.00	0.00	1.53	46.22	1.36	0.00	0.00	1.16	23.06
gen-10	2.71	0.00	0.00	1.65	46.31	1.32	0.00	0.00	1.64	24.06
gen-15	2.70	0.00	0.00	1.78	46.55	1.32	0.00	0.00	2.12	24.22
gen-20	2.70	0.00	0.00	1.92	46.37	1.55	0.00	0.00	2.65	25.45
gen-25	2.73	0.00	0.00	2.01	46.74	1.54	0.00	0.00	3.18	27.39
gen-30	2.71	0.00	0.00	2.16	46.73	1.53	0.00	0.00	3.68	28.79
stor-05	2.75	0.00	0.00	1.54	46.19	1.31	0.00	0.00	0.87	23.48
all-05	2.76	0.58	2.73	3.99	45.44	1.49	0.95	2.70	3.60	26.07

Table 3.9: Impact of imperfect information on individual bills (flexible agents only) and provider revenues

Scenario	Winter case					Summer case				
	Change in provider revenues $\tilde{\Phi}^{\star}_{\mathcal{A}} - \Phi^{\star}_{\mathcal{A}}$ (\$)	Change in individual charges $\tilde{\Psi}^{\star}_{j} - \Psi^{\star}_{j}$ (\$)				Change in provider revenues $\tilde{\Phi}^{\star}_{\mathcal{A}} - \Phi^{\star}_{\mathcal{A}}$ (\$)	Change in individual charges $\tilde{\Psi}^{\star}_{j} - \Psi^{\star}_{j}$ (\$)			
		min	med	mea	max		min	med	mea	max
cons-05	166.09	-0.87	0.01	0.61	24.29	75.35	-5.55	0.05	0.29	20.71
cons-10	184.19	-0.69	0.04	0.67	26.59	87.39	-1.95	0.08	0.34	24.72
cons-15	190.07	-1.63	0.07	0.70	25.24	131.83	-5.23	0.18	0.51	19.76
cons-20	205.88	-3.35	0.10	0.75	26.10	119.01	-4.12	0.20	0.46	17.34
cons-25	233.72	-5.02	0.11	0.86	26.97	115.24	-8.21	0.17	0.44	27.99
cons-30	223.42	-3.92	0.16	0.82	25.85	175.44	-8.01	0.17	0.68	22.42
gen-05	161.15	-0.08	0.00	0.59	24.79	72.25	-0.51	0.00	0.28	21.08
gen-10	161.32	-0.20	0.00	0.59	24.78	63.35	-2.52	0.00	0.24	21.27
gen-15	159.57	-0.40	0.00	0.58	24.82	72.92	-1.51	0.00	0.28	21.81
gen-20	161.64	-0.57	0.00	0.59	24.70	67.60	-3.14	0.00	0.26	23.49
gen-25	161.65	-0.91	0.00	0.59	24.92	79.09	-5.42	0.00	0.31	18.08
gen-30	161.82	-0.78	0.00	0.59	24.71	105.36	-3.92	0.00	0.41	17.32
stor-05	161.10	-1.50	0.00	0.59	24.04	66.60	-1.88	0.00	0.26	21.04
all-05	171.43	-1.71	0.02	0.63	23.98	70.57	-4.64	0.03	0.27	20.34



(a) Winter case.



(b) Summer case.

Figure 3.8: Distribution of the impact of imperfect information on individual bills across the flexible agents.

contribution of each residential prosumer in achieving the team optimum.

Simulation results obtained for two test cases based on historical data demonstrate the proposed approach. In both cases, the proposed pricing scheme allows us to induce an aggregated energy exchange schedule within 2% of the ideal schedule initially selected at the economic dispatch stage. The impact of imperfect information on the energy usage magnitude is also assessed. The sensitivity analysis performed shows that the aggregated error remains below 4% across the various scenarios considered. However, imperfect information leads to increases in individual bills. Additional investigations will be required to examine more complex scenarios testing for uncertainty on magnitude *and* time.

3.9 Proof I

Proposition 1. *Constraints* (34) *are a necessary and sufficient condition for prosumer $j \in J$ to satisfy his energy consumption requirements over $\mathcal{T}$.*

It is obvious that constraints (34) are necessary for end-user j to satisfy his energy requirements over $\mathcal{T}$. To prove that these constraints are also sufficient, think of each interval t_3, t_4 for which the corresponding dd variable is nonzero as a job that must be completed. Each job has a release time (start of period t_3) and a due date (end of period t_4). The prosumer has given amounts of energy to expend each time period t, namely y_{jt}. For each t, the prosumer can choose how to allocate that period's energy among the jobs. Energy can only be allocated to a job that has been released and whose due date has not passed. We want to prove that if constraints (34) are satisfied, then it is feasible for the prosumer to allocate energy so as to complete each job by its due date.

Proof. Step 1. The earliest due date rule, EDD, finds a feasible solution for the prosumer if one exists. (EDD assigns energy to the job with earliest deadline, among all jobs that have been released but not completed. Ties are broken arbitrarily. If that job is completed and more energy remains, the EDD rule is repeated until either all released jobs are completed or no energy remains.) Proof: Consider any feasible schedule that is not EDD. At some time t, some released job with due date h gets a unit of energy that could be given to a different released job with due date $h' < h$. Since the schedule is feasible, both jobs are eventually completed. Trade a unit of energy from the former job to the latter at time t for a unit of energy that that latter eventually gets at some time t' after t. The modified schedule remains feasible because the former job gets its unit of energy at time $t' \leq h < h'$, i.e. before its due date, and because the latter job was released by time t. Repeat this modification until the schedule is EDD.

Step 2. Replace each job that requires $g > 1$ units of energy with g jobs that each require one unit. Among all possible cases in which each job requires one unit of energy, consider a minimal counterexample, a smallest case for which the constraints (34) are satisfied but no feasible solution for the prosumer exists. If the counterexample has a one-period job for some period t, remove the job and reduce the available energy during t by 1. (Notice there must be available energy because the constraint is satisfied). This is equivalent to forcing the schedule to complete that job. Since there was no feasible solution at all, there can't be a feasible solution to this more restricted case. The constraints (34) are satisfied after the job and unit of energy are removed, because for every t_1, t_2 for which the left-hand side is reduced by 1, so is the right-hand side. But then we would have a smaller counterexample, contradicting minimality. Therefore the counterexample has no one-period jobs.

Step 3. By step 1, EDD fails to find a feasible solution. Let T be the first time period at the end of which some job is due, but is not completed by EDD. We claim that the minimal counterexample has no jobs due later than T. If it did, those jobs could be removed. Constraints (34) would remain satisfied because the left-hand side does not change, and the right-had side stays the same or decreases. But that would create a smaller counterexample, contradicting minimality.

Step 4. We claim that no energy is available after period T. Since no jobs are due after T, all constraints with $t_4 \leq T$ are satisfied without using energy after T. If the counterexample continued beyond period T, it could be truncated. That truncation would contradict minimality.

Step 5. We claim that no energy is available during period T. If a unit of such energy exists, remove it and remove a job with start date t and due date T, where t is the maximum possible value for which such a job exists. (At least one job with due date T must exist, by step 3.) We will show that these removals produce a counterexample. That will contradict minimality. The removals could fail to produce a counterexample in two ways. First, the removals could result in a case for which the prosumer has a feasible solution. Second, the removals could violate a constraint (34). The first is impossible for the same reason given in step 2. The removals are equivalent to assigning a particular unit of energy to a particular job. Since the counterexample has no feasible solution, there can be no feasible solution after restricting the counterexample to force this particular assignment. Consider the second kind of possible failure. Removal of the energy unit from period T can only render a constraint from (34) with $t_2 = T$ infeasible, since by step 4 the counterexample ends at period T. Suppose constraint t_1, T becomes infeasible after the removals. If $t_1 \leq t$, the right-hand side of the constraint also decreased by 1 because job t, T was removed. Hence if $t_1 \leq t$ the constraint does not become infeasible. However, if $t_1 > t$ then by the maximality of t there are no jobs of form t_3, T for any $t_3 \geq t_1$. Constraint (34) for $t_1, T-1$ is feasible in the counterexample, hence is feasible after the removals (which don't change either left or right hand sides). The right-hand side of (34) for t_1, T is the same as for $t_1, T-1$ because no jobs $\geq t_1, T$ exist. Hence constraint (34) for t_1, T is feasible after the removals. Hence the second kind of failure can not occur, either.

Step 6. By step 5, for all t_1 the constraint (34) for t_1, T is satisfied using energy available from t_1 to $T-1$. Take all jobs due at T and make them due at $T-1$. The t_1, T constraint becomes the new $t_1, T-1$ constraint, and hence is satisfied. We have a smaller counterexample, which contradicts minimality. The base case of this downwards inductive proof has $T = 1$ and is obvious. □

3.10 Proof II

Theorem 4. *Given integer matrix A and vector b, rational vector u such that $Au \leq b$, and scalar d, it is strongly NP-complete to determine if the polyhedron $\{x|Ax \leq b\}$ has an extreme point v such that $||v-u|| \leq d$, where "$||\ ||$" denotes either the Euclidean norm or the L_1 norm. Moreover, it is strongly NP-complete to find an approximate solution to this problem with any constant-factor guarantee.*

Proof. The reduction is from 3-partition, which asks, given integer weights $w_i : i \in I$, whether there exists a partition of I into 3-tuples such that sum of weights in each 3-tuple equals $w^* \equiv 3\sum_{i \in I} w_i/|I|$.

Let $J = \{1, 2, \ldots, |I|/3\}$. Define for all $i \in I, j \in J$ variable x_{ij} which represents whether or not weight i is placed in 3-tuple j. Define additional variables $y_j : j \in J$ which represent the total weight of 3-tuple j. Define the polyhedron P by the constraints

$$0 \leq x_{ij} \leq 1 \qquad \forall i \in I, j \in J \tag{60}$$

$$\textstyle\sum_{i \in I} x_{ij} = 3 \qquad \forall j \in J \tag{61}$$

$$y_j = \textstyle\sum_{i \in I} w_i x_{ij} \quad \forall j \in J \tag{62}$$

The polyhedron P' defined by constraints (60,61) is a b-matching polytope, which is well-known to be totally unimodular and such that each b-matching corresponds to an extreme point. Since constraint (62) imposes no further constraints on the x_{ij} and sets the y_j variables to be linear combinations of the x_{ij}, there is a $1-1$ correspondence between the extreme points of P and their projections onto the extreme points of P'.

By total unimodularity each extreme point of P' corresponds to a an integer solution of constraints (60,61). Therefore each extreme point in P corresponds to a partition of I into 3-tuples given by the x_{ij} variables together with the vector y of resulting 3-tuple weights. As a consequence, there exists an extreme point in P with $y_j = w^* \; \forall j \in J$ iff the answer to the instance of 3-partition is "yes."

Define $u = (x, y)$ with

$$x_{ij} = \frac{3}{|I|} = \frac{1}{|J|} \; \forall i, j; \quad y_j = w^* \; \forall j \in J.$$

By definition of w^*, u satisfies constraint (62) and hence $u \in P$. The projection of u onto P' is equidistant to all extreme points of P' because every extreme point has $|I|$ components of x equal to 1, and the rest equal to 0. For every extreme point of P, the value $||u - v||$ depends only on how the y_j components differ. To be precise, there exists a valid 3-partition of the weights w_i iff P contains an extreme point at distance from u equal to

$$|I|(|J| - 1)/|J| + |I|(|J| - 1|/|J| = 2(|I| - 3)$$

for the L_1 norm, and

$$\sqrt{\frac{|I|(|J| - 1)}{|J|^2} + \frac{|I|(|J| - 1)^2}{|J|^2}}$$

for the L_2 norm. Otherwise, the nearest extreme point of P is farther away from u.

How hard is approximation? Let $\alpha > 0$ be arbtitrary. Consider the L_1 norm. Scale the w_i values by an integer $M \geq \alpha|I|$. The closest extreme point of P to u will have distance $\leq 2|I|$ (and roughly equal to that) if the 3-partition has a solution, and will have distance $> M$ (roughly $M + 2|I|$) if not. Therefore, if we could find an extreme point within a factor α of the closest one, we could solve 3-partition. This proves that it is NP-hard to approximate the nearest vertex problem to within any constant α. $\square$

3.11 Proof III

Theorem 5. *Let $P \subset \Re^n$ be a polyhedron defined by inequalities $Ax + By \leq b$. Let $\hat{P}$ denote the projection of P onto the y variables. It is strongly NP-complete, given $y^* \in \hat{P}$, to determine whether or not there exists an extreme point (x, y) of P such that $y = y^*$. Hence it is strongly NP-complete to determine whether a point is uniquely exposable in the weak sense.*

Proof. The reduction is from X3C, Exact 3-Cover. An instance of X3C comprises a collection S of 3-tuples of a ground set G. An exact 3-cover is a subset $S' \subset S$ that partitions G, that is, such that $|S'| = |G|/3$ and $\cup_{s \in S'} s = G$. X3C remains NP-complete when restricted to instances such that every element of G appears in the same number of elements of S. Let $x_s : s \in S$ equal 1 if s is chosen to be in S' and 0 if not. The corresponding LP constraints are $0 \leq x_s \leq 1$. All other constraints will be equality constraints that define additional variables in terms of the x_s variables, so the set of extreme points of P will correspond to the extreme points of the $|S|$-dimensional hypercube. Let $B_{sg} = 1$ if s contains $g \in G$ and 0 otherwise. To check for an exact 3-Cover, define additional variables $y_g : g \in G$ by $y_g = \sum_{s \in S} = B_{sg} x_s$. Then $y_g = 1 \forall g$ iff the x_s variables define an exact cover. It remains to verify that $y^* = (1, 1, \ldots, 1) \in \hat{P}$. Let $x^* = \frac{|G|}{3|S|}(1, 1, \ldots, 1)$. Then $(x^*, y^*) \in P$ so $y^* \in \hat{P}$. Since X3C is strongly NP-complete, the proof is complete. $\square$

CHAPTER IV

A CROSS-BOUNDARY APPROACH FOR THE CO-PRODUCTION OF GRID ARCHITECTURE MODELS

4.1 Introduction

Over the past decade, in the U.S., the modernization of the national electricity grid has taken the form of a technology-led transformation. As early as 2004, the U.S. Department of Energy (DOE) released a National Electric Delivery Technologies Roadmap to guide technology development [31]. This strategic planning effort was rapidly articulated around desired grid characteristics [111, 152, 153]. Finally, Congress directed the National Institute of Standards and Technology (NIST) to develop technology standards that facilitate interoperability between the various grid components [115].

Along with these efforts towards technology planning and coordination, the American Recovery and Reinvestment Act of 2009 provided $4.5 billion in appropriations for programs stimulating the research, development, demonstration and deployment of smart grid technologies. At the same time, new energy innovation institutions focused on particular technology states were established including the Advanced Research Projects Agency-Energy division (ARPA-E), the Energy Frontier Research Centers (EFRCs), and the Energy Innovation Hubs [108, 109].

A decade after the launch of the "Grid 2030" initiative [30], significant progress has been made towards the deployment of key enabling technologies including grid-connected distribution generation and storage, transmission and distribution automation, advanced meters and advanced measurement technology [152, 153].

However, a comprehensive vision for the future electricity grid as a whole is yet to be developed. The initial intent to co-develop the future architecture of the grid along with new technologies [30, p. 14] remains largely unrealized; instead, the development of multiple technology-oriented programs has been prevailing. Desired properties for the future grid have been identified [111, 152], but there is no literature proposing an architecture that demonstrates these characteristics. The need for developing a common information model to represent the future grid has been identified [35], but this need is still largely unmet and is not prioritized as such (e.g.: [11, 101]).

In the context of this chapter, an 'architecture' –or 'system architecture'—for the future grid consists of a set of specific architecture models. Such models, as defined in systems engineering, can be used to operationalize the concept of 'vision' for the future grid. They include objective models (reflecting the grid objectives), models of form (the elements and interfaces constituting the grid), functional models (how the grid behaves), performance models (how effectively are the objectives satisfied), and managerial models (process describing the transition to the future grid, and the way it will be managed) [93].

This chapter attempts to answer the following questions: (1) Why is a new architecture for the future U.S. electricity grid needed? (2) Why has such an architecture not emerged over the past decade? and (3) Should policy makers try to facilitate this development process, and if so, how?

First, we document the need for new grid architecture models (section 4.2). We identify three factors that make the development of such models a necessary requirement towards grid modernization: (1) the increasing collaborative nature of the grid, (2) the blurring of boundaries between the various disciplines concerned with the grid, and (3) the blurring of functions performed by some of the grid components. We argue that the lack of a comprehensive and shared vision for the future electricity grid is a significant barrier to the effective modernization of the U.S. electricity system.

Second, we frame the grid architecture problem –namely the absence of grid architecture—as both a market failure legitimizing government intervention, and a problem-of-problems –or meta-problem—requiring the development of non-conventional methods of solution (section 4.3). We conceptualize the substantive problem as distances –spatial, temporal, conceptual and cultural– that prevent the various communities-of-practice involved to effectively cooperate.

Third, we propose a policy approach to address the grid architecture problem. We introduce the notions of broker and boundary object that serve as a theoretical framework for the proposed approach (section 4.4). We illustrate how this framework can foster cross-disciplinary research work on the future electricity grid based on an experiment conducted at the research group level (section 4.5). We propose to scale up this experiment using the concept of boundary organization (section 4.6).

Our work, focused on the U.S. case, is primarily directed to national and international policymakers involved in either assessing existing programs or designing new policy initiatives that support the modernization of electricity grids from a system-level perspective. It also provides insights relevant to any stakeholder concerned with the development of new architecture models for future electricity grid.

4.2 The need for architecture models

In this section, we first identify and discuss three factors motivating the development of new architecture models for the future electricity grid. We then review the recent efforts to develop such models and analyze their limitations.

4.2.1 The electricity grid: an evolving system-of-systems

Since the early days of electricity, the U.S. national grid has mostly evolved incrementally through variations and extensions of original architectures that had proved by use to be sound, such as the Westinghouse concept of universal supply system [71]. At the same time, the U.S. grid has never been a monolithic system: many of its components –in particular the local distribution systems—can be seen as systems in their own right. They are acquired, integrated, and managed separately; they interact to provide functions not provided by any of the components alone; and in some cases, they continue to operate and fulfill their own valid purposes if disassembled from the overall system.

Over the past decade, new types of grid components enjoying relative operational and managerial independence have emerged. Most of these components have finer granularity than distribution systems, the traditional finest level of managerial authority. This change suggests that the "system-of-systems" [94] nature of the U.S. national grid, which is not new, will increase in complexity due to an increasing number of system components.

Electric vehicles are among those new components. Their primary purpose is to transport individuals and goods, but they may also provide support services to the grid [148, 58]. Home energy management systems (HEMS) are yet another example. HEMS follow their own, local objectives, but may also contribute to the objectives assigned to the whole system [70].

Therefore, the normal operational mode of many of the future grid components will *not* be subordinated to any central authority, contrary to "directed" systems-of-systems [94] (Fig. 4.1). However, will these system components collaborate to fulfill some agreed-upon central purposes ("collaborative" system-of-systems)? Or will the future electricity grid lack both a central management authority *and* centrally agreed-upon purposes ("virtual" system-of-systems)?

Virtual systems-of-systems fulfill purposes that are dynamic and change at the whim of the users. New purposes and corresponding behavior may arise at any time, including unexpected or undesired ones. The long-term nature of such systems is determined by highly distributed and partially invisible mechanisms [94]. A transformation of the U.S. national grid into a virtual system-of-systems could undermine the stability of grid operations, and eventually threaten national security, a centrally

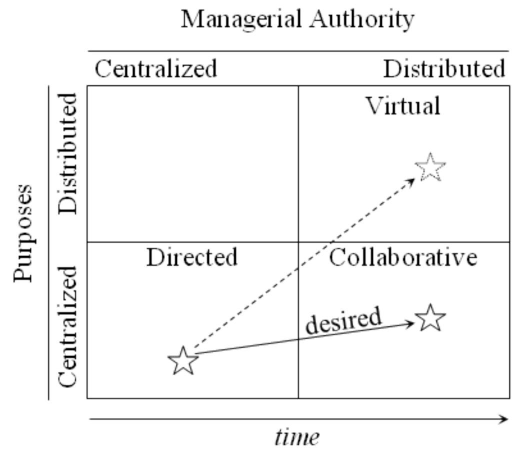


Figure 4.1: Three different forms of managerial control for the national electricity grid modeled as a system-of-systems.

agreed-upon purpose par excellence.

Thus, the future electricity grid must be architected to ensure a safe evolution towards a collaborative system-of-systems that continues to perform at least *some* centrally agreed-upon purposes (Fig. 4.1). This architecture must ensure that grid participants have the right incentives to collaborate. It may also specify some predetermined rules-of-engagement to keep the system operations stable over time. In this context, architecture models for the future electricity grid appear both as a necessary set of tools to guide the evolutions of the grid through technically, economically and politically stable intermediate forms, and as a structure around which future collaboration will take place.

Furthermore, to ensure effective collaboration among the future grid participants, we claim that such architecture must result from a cooperative decision-making process involving the various stakeholders concerned with the grid. This chapter attempts to characterize the complexity of this cooperation process and analyzes how it could possibly be expedited.

4.2.2 Blurring of knowledge boundaries

The notion of cooperation implicitly implies both the existence of boundaries that mark the limits of a subject or a sphere of activity, and the intention to work across these boundaries to produce or create something. The grid was initially designed as a combination of electric components that distributed electric light to the public using a central-station supply approach (e.g.: [71]). Since then, it has gradually evolved into a system that overcomes the boundaries of traditional engineering disciplines (Table 4.1).

This evolution towards cross-disciplinary involvement relates, first, to the goals assigned to the electricity grid. In the aftermath of the 1973 oil crisis, these goals started to become multidimensional, with new goals including energy security, economic growth and environmental protection (see for instance the Declaration of Findings and Purposes in the Department of Energy Organization Act of 1977). These goals were reaffirmed in the Energy Policy Act (EPA) of 2005, the Energy Independence and Security Act (EISA) of 2007, and the American Recovery and Reinvestment Act (ARRA) of 2009. Addressing these multiple goals required knowledge in multiple disciplines including electrical engineering, but also mechanical engineering, material science, communications, controls, optimization, computing, environmental science, public policy, law, and finance. Second, this increasing involvement of multiple disciplines also resulted from the "highly arbitrary" organization of knowledge into disciplines [15] that often reflects social conventions (e.g.: [53]), leading systems such as the electricity grid to develop in interdisciplinary gaps. Consequently, the U.S. grid progressively became a multidisciplinary system with multiple disciplines working on some of its aspects in parallel or sequentially, but rarely challenging their boundaries.

In 2003, the "Smart Grid 2030" initiative aimed to go one step further by bringing together members from different disciplines to develop shared goals for the modern grid and generate new common methodologies, perspectives, and knowledge [30]. This resulted in the identification of desired properties of the modern grid, and the development of metrics for measuring progress towards implementation of smart grid technologies, practices, and services [111, 152, 153].

The next logical step consists of moving from interdisciplinarity to transdisciplinarity –the most advanced degree of involvement of multiple disciplines [27]–and encourage scientists from relevant disciplines, non-scientists and other stakeholders to develop a shared conceptual framework for the grid –a vision, an architecture– that transcends the disciplinary boundaries and looks at the dynamics of the whole electricity grid in a holistic way.

This move towards transdisciplinarity has emerged organically; it is not a goal in itself but a consequence [86] of the more complex set of objectives pursued at the system level since the 1970s, and of the arbitrariness of disciplinary boundaries. Yet, the lack of architecture models for the future grid is evidence that this move towards transdisciplinarity is incomplete, resulting in a form of inefficiency. Architecture models are the missing link between the various disciplines involved in the modernization of the U.S. grid. They are required, not only as a set of tools guiding the electricity system evolutions or as a structure ensuring future collaboration among actors, but also as a new ontology that transcends the existing knowledge boundaries and creates a common universe of discourse between the various actors involved in the modernization of the grid.

4.2.3 Blurring of functional boundaries

Architecture models for the future grid can be seen as a shared conceptual framework that transcends the disciplinary boundaries. They also constitute simplified representations of the grid as a cyber-physical system that matter when it comes to decide what the future grid will look like.

Table 4.1: Temporal evolutions of the degree of involvement of the various disciplines concerned with the electricity grid

Degree of involvement	Disciplinary	Multi-disciplinary	Inter-disciplinary	Trans-disciplinary
Graphical analogy				
Time	End of 19th century	1970s energy crisis	Early 2000s	Emerging
Description	The grid is conceived by power engineers as a combination of electric components. The initial purpose is to distribute electric light to the public using a central-station supply approach.	The goals assigned to the grid progressively become multi-dimensional leading multiple disciplines to work on some aspects of the grid in parallel or sequentially.	Development of shared goals for the modern grid. New common methodologies, perspectives, and knowledge are developed.	Development of a holistic conceptual framework for the future electricity grid that transcends the disciplinary boundaries.

In decision-making, the concept of bounded rationality is the idea that rationality of individuals is limited by the information they have, the cognitive limitations of their minds, and the finite amount of time they have to make a decision [134]. Because decision-makers lack the ability and resources to arrive at the optimal solution, they instead apply their rationality only after having constructed simplified models of real-life situations [136].

In the electricity industry, the simplified model that has traditionally been in use to describe the grid divides the electricity system into four main categories: generation, transmission, distribution, and energy utilization. This classification dates back from the Westinghouse concept of universal supply system displayed at the Chicago exposition of 1893 and first implemented at the Niagara Falls [71]. The use of the four-category model has extended well beyond the boundaries of engineering disciplines. For instance, the electricity value chain in power systems economics is traditionally characterized using the four-category representation. Specific policies and policy institutions have also been developed over time for each of the four segments.

It is notable that in all the major planning reports or roadmaps released over the past ten years in the U.S., including [30, 31, 111, 152, 153, 101, 11], new objectives, new properties, new functionalities for the electricity grid are discussed, but the underlying model on which the stakeholders project their goals, problem formulations and solutions is always –implicitly or explicitly– the four-category model.

Consistent with Henderson and Clark's work on architectural innovation, we argue that the "architectural knowledge" relative to that dominant design has become so deeply embedded in the structure and information-processing procedures of the various organizations concerned with the electricity grid that they have progressively lost their ability to learn new "architectural knowledge", or even recognize the emergence of new designs in their environment. Instead, these organizations have mostly been focused on learning new "component knowledge" to improve the particular components of the dominant design [63].

Yet, the dominant, four-category representation is becoming less and less accurate to serve as a simplified model for the grid because the realities it represents have been changing.

First, a new function, energy storage, is emerging [33]. This new function, central in the future grid, does not fit into the traditional representation.

Second, there has been an emerging trend over the past decade to move from four differentiated categories of entities, each limited to perform one function, to undifferentiated entities performing multiple functions. This blurring of functional boundaries is particularly noticeable at the end-user level: while end-users were in the past limited to consume electricity, they can now produce (e.g., solar panels), store (e.g., stand-alone storage system, EV battery), and even inject electricity back into the grid [70]. The traditional classification model does not accommodate for these developments.

Third, the electrical grid has evolved from a vertically-integrated physical system –limited to carrying electrons from generation units to end-users– to a complex set of distributed cyber-physical systems equipped with new communication [59] and computational capabilities [163]. This move towards increased operational and managerial independence (Fig. 4.1) comes with a significant fragmentation of the decision-making entities concerned with the operation and planning of the grid. The traditional representation of the grid, describing a purely electric and vertically integrated system, does not reflect all these recent developments, making it necessary to develop new simplified models for the future electricity grid.

We now discuss several limitations of the recent efforts to address the need for new grid architecture models.

Table 4.2: Factors motivating the development of architecture models for the future electricity grid

Key factor	Role of architecture models
Increasing collaborative nature of the grid	Guide the future evolutions of the grid through stable intermediate forms, and serve as a structure around which future collaboration will take place.
Blurring of knowledge boundaries	Provide a new ontology that transcends the existing knowledge boundaries and creates a common universe of discourse between the discussants involved in grid modernization efforts.
Blurring of functional boundaries	Offer a simplified but accurate representation of the grid that accommodates for the new storage function and the emerging decision-making entities performing multiple functions.

4.2.4 Developing architecture models: limitations of recent efforts

Over the past decade, the need to facilitate communication and cooperation between the various stakeholders through the development of common models has been recognized. For example, a "common representation of information models for the smart grid" has been identified as an important pre-requirement to any attempt to develop a comprehensive vision for the future electricity grid [35]. But a number of limiting factors have undermined the recent efforts.

4.2.4.1 Definition vs. characterization

The action of defining what the future grid architecture should look like and the action of describing its desired properties have frequently been confused. All the major planning –or so called 'vision'– documents that we reviewed, including [30, 31, 111, 152, 153, 101, 11], are limited to a description of some of the desired characteristics of the future grid in lieu of a comprehensive definition of its future architecture. The future grid was sometimes even presented as "defined by its characteristics" [112]. This first confusion did not facilitate the emergence of architecture models; we show in section 4.4 that it can be further explained by the ill-defined nature of the grid architecture problem.

4.2.4.2 *Architecture, interoperability and standards*

The loose use of the term architecture generated additional difficulties. In particular, the term architecture has often been confused with the related –but distinct– concepts of *interoperability* and *standards*. For instance, the terms architecture, standards and interoperability are grouped under the same metric in the U.S. Department of Energy (DOE) smart grid reports [152, 153].

Interoperability is the ability of two or more systems or components to exchange information and to use the information that has been exchanged [72]. Interoperability is therefore a property of a system and often results from the implementation of *standards* [73]. Open standards in particular can facilitate interoperability [42]. A system architecture may also support the interoperability of the system's components, such as service-oriented architectures [7]. However, strictly speaking, the notion of interoperability does *not* apply to system architectures, but only to the systems or components they represent.

4.2.4.3 *Legacy representations*

Over the past decade, the National Institute of Standards and Technology (NIST) has been one of the very few organizations in the U.S. to make tangible, publicly-available contributions towards the development of a system architecture for the future electricity grid. In particular, the NIST conceptual model developed and maintained by the Smart Grid Interoperability Panel (SGIP) –a public-private partnership established by NIST—constitutes the one notable attempt to mitigate the rigidity of the traditional, four-category representation of the grid [115]. The NIST model was subsequently extended by the Smart Grid Coordination Group (SGCG), the European counterpart of the SGIP [22].

Although this model constitutes a valuable first step, it is important to recognize that the NIST model is essentially limited to extend the traditional representation by building additional categories on top of the four traditional categories (Fig. 4.2). The NIST model also fails to address the blurring of functions discussed above. In the longer term, relying on such legacy representation to characterize the future grid may prevent effective collaboration among the future grid participants in that it does not fully reflect the functional changes that are currently taking place. It may also re-enforce "path dependency" by limiting the rate of integration of radically new ideas –in particular new architectural knowledge—possibly leading to technological lock-in.

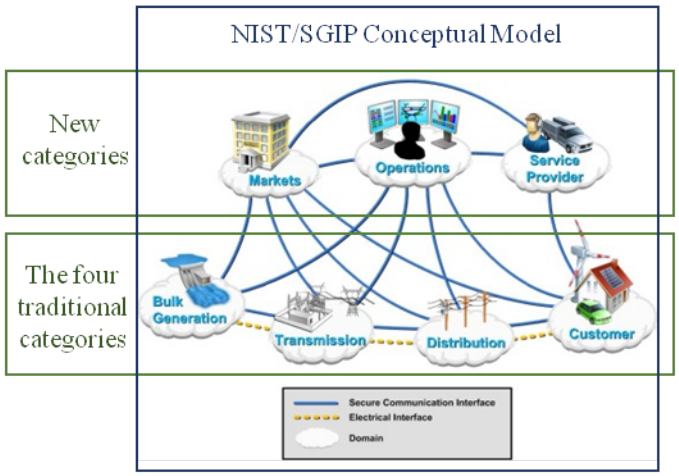


Figure 4.2: The NIST/SGIP conceptual model decomposed into traditional and new categories.

4.2.4.4 Predominance of interoperability considerations

Since its inception by NIST, the SGIP has approached the development of new architecture models primarily as a means to enable interoperability. This is consistent with section 1305 of the EISA of 2007 which mandates NIST to coordinate the development of a smart grid interoperability framework. However, from a policy standpoint, interoperability is *not* in itself a primary goal of the future electricity grid. Enabling interoperability is important only in that it contributes to the broader economic, environmental and social goals that motivate the modernization of the U.S. grid.

This confusion in the hierarchy of objectives can be further observed in the formulation of the EISA. Section 1305 motivates the development of an interoperability framework only by the need to "enable all electric resources, including demand-side resources, to contribute to an *efficient*, *reliable* electricity network" (emphasis added). Increased efficiency and reliability are indeed desired properties that can be improved through interoperability. But the future grid also has broader objectives –including energy security, economic growth and environmental protection—that could greatly benefit from the development of new architecture models, making the focus on interoperability too narrow and limiting.

The subordination of architecture development to smart grid interoperability reflects more generally the fact that none of the three energy-related bills passed over the past decade in the U.S. –the EPA of 2005, the EISA of 2007, and the ARRA of 2009– formally recognized that the development of architecture models is a necessary condition to achieve the goals assigned to the future electricity grid.

4.3 Framing the grid architecture problem

4.3.1 The absence of architecture: a market failure

4.3.1.1 Characterization

From a public policy perspective, the difficulty to converge to a shared vision for the future electricity grid can be framed as a market failure by either focusing on *externalities*, or by examining the *public good* nature of the grid architecture.

The development of a shared vision for the future grid can be seen as a 'chicken-and-egg' problem. Any architecture development requires some sense of the technology available to ensure effective implementation. Developing that technology requires in turn that the desired functionalities of the future architecture have been identified. As soon as the architecture is defined, the technology enabling the corresponding functions can be developed and implemented. In that sense, the development of architecture models for the future grid generates *positive externalities* that affect all the stakeholders involved.

Another approach to characterize the absence of grid architecture as a market failure consists of considering the architecture itself as a good and examining its nature. An architecture model is a piece of information, and consumption of information is non-rivalrous –one person's consumption does not interfere with another's. In addition, the architecture of the future grid is not excludable in use since it must result from a cooperative design process and remain 'open source' to achieve its purpose of developing a shared vision that provides to the future grid participants the right incentives to collaborate. Thus, architecture models for the future grid have *pure public good* attributes [13]. Pure public goods are generally not supplied by markets because of the inability of private providers to exclude those who do not pay for them [157, 160]. In the literature, other aspects of electricity grids have also been characterized as public goods such as network reliability [121] or more generally the security of electricity supply [1].

4.3.1.2 Consequences

Valuation and free-riding problems arise from the public good nature of the architecture of the future grid. The various stakeholders receiving some level of positive benefits from the development of architecture models do not have any incentive to reveal honestly the magnitude of these benefits (valuation problem). If contributions for developing architecture models are to be based on benefit levels, stakeholders have an incentive to understate their benefit levels; if contributions are not tied to benefit levels, they may overstate their benefit levels.

The possibility of free-riding also discourages honest participation. If a given stakeholder does not contribute and everyone else does, the architecture models provided, from which he cannot effectively be excluded, will be essentially the same as if he did contribute (free-riding problem). On the other hand, if he contributes and others do not, architecture models will not be provided anyway. Either way our stakeholder is better off not contributing. Both valuation and free-riding problems tend to be worse in larger groups of stakeholders [160] as it is the case with the electricity grid (cf. Appendix 4.8).

The inability of private markets to develop and provide architecture models for the future electricity grid is a market failure that legitimates government intervention and requires the use of nonmarket mechanisms. Generic policy alternatives include direct supply by government bureaus or independent agencies, or indirect supply through contracting. But beyond the form of government intervention –direct or indirect– is the question of the actual solution method to develop such architecture models. Nonmarket outputs –such as architecture models for the future grid– are often hard to define [165]. There is no standard production technology to develop such non-market outputs, no evaluation mechanism equivalent to profit or loss for appraising success, no specified procedure for terminating unsuccessful production. This calls for a more in-depth examination of the nature of the architecture problem.

4.3.2 Developing a grid architecture: a meta-problem

Defining what the future grid should look like is a planning task that presents characteristics typical of a particular class of policy problems referred to as "complex", "messy", "ill-defined", "squishy", or "wicked" in the literature [95, 141, 124, 138].

The foremost characteristic of the grid architecture problem is that it has no definitive formulation. Each of the various interest groups defines the problem differently according to their own objectives and values. Because there is no definitive problem statement, the various discussants often jump directly from their understanding of the energy challenges to a range of solutions addressing their objectives, and their problem formulation. For some, environmental concerns –such as climate change or negative impacts on ecosystems– are the problem. Smart grid technologies with positive environmental impacts should therefore be an important point of focus [113, 65]. For others, reliability [106], efficiency and affordability are the key metrics; for them, the future grid should be an 'optimized' grid. For some others, economic benefits [97], security and privacy issues [96, 83], or job creations [159] are critical indicators to monitor as the grid is being modernized. The grid architecture problem therefore appears to be a meta-problem –a problem-of-problems– that is ill-structured because both the problem boundaries and the problem representations held by the diverse stakeholders seem to be "unmanageably huge" [34, p. 83].

Other characteristics of "wicked" problems as defined by Rittel and Webber [124] are present. The definition of what the future grid should look like has no stopping rules since it is hardly possible to design and implement a grid that is at the same time fully reliable, secure, and highly efficient while providing electricity at affordable costs, preserving the environment, and supporting energy independence. The goals pursued are multidimensional: they inevitably conflict with each other and require trade-offs. Additionally, there are no 'right' solutions since each technology has advantages and disadvantages. In the case of electricity generation for instance, fossil-fueled technologies are comparatively cheap [155] but pollute more; nuclear energy is emissions-free but presents risks; solar or wind technologies are renewable but intermittent. Finally, every solution component is a 'one-shot operation' that leaves traces that can hardly be undone: the construction of a power plant takes several months or years and has important upfront costs [154]; the adoption of new market and policy regulations leads entire sectors to change their strategies; enabling communication with electricity customers requires the large-scale deployment of smart meters.

Thus, we argue that the grid architecture problem is both a market failure and a meta-problem. We now propose a formulation for the substantive problem.

4.3.3 Formulating the substantive problem

4.3.3.1 From disciplines to communities-of-practice

The move towards transdisciplinarity in the context of the electricity grid suggests that traditional disciplines –with somewhat artificial boundaries—are in fact not the right level of analysis to understand how cooperation could be fostered to facilitate the emergence of a shared and comprehensive vision for the future grid. Instead, the recent literature suggests considering communities-of-practice as the fundamental unit of analysis (e.g.: [135]).

Communities-of-practice are formal or informal groups of actors. Within each group, members share a common domain of interest, engage in joint activities, and develop a shared repertoire of resources [162]. The concept of community-of-practice allows for describing the social complexity inherent to the electricity grid at multiple levels of scale. At the local level, each of the organizations concerned with the electricity grid contains multiple communities-of-practice. At the system level, communities of practice may also cross formal organizational or institutional boundaries. This community-based decomposition is therefore scale-invariant and can be proposed to map the complexity of the various stakeholders involved (Fig. 4.3).

4.3.3.2 Barriers to cooperation between and within communities

The increasing involvement of multiple organizations, disciplines, and communities-of-practice presents both opportunities and challenges for the future electricity grid.

Among the opportunities is the fact that innovation is fostered by cooperation and knowledge sharing across disciplinary, professional or organizational boundaries [38, 17, 18, 77, 87]. The large and diverse set of stakeholders involved in the modernization of the U.S. national grid is therefore a tremendous opportunity.

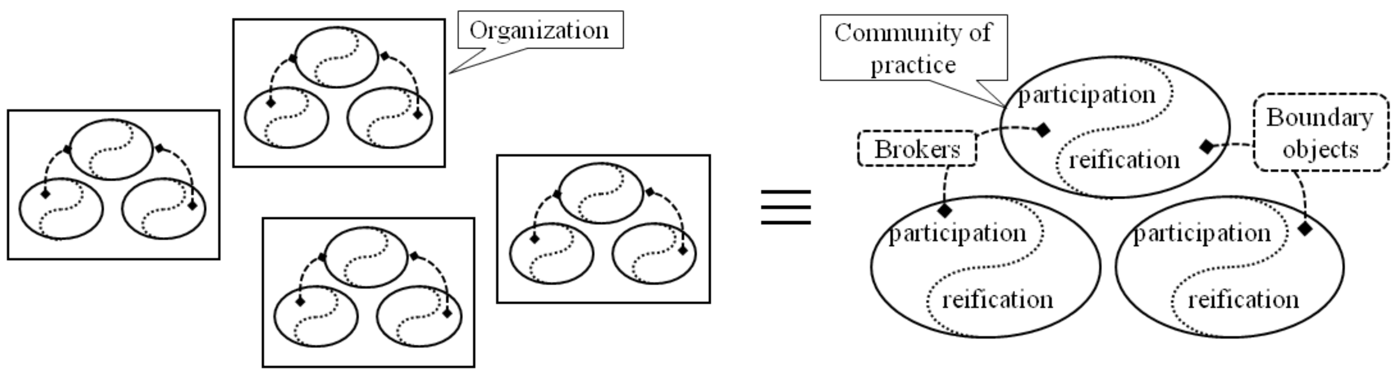


Figure 4.3: Scale-invariant community-based decomposition of the stakeholders involved in the development of architecture models for the future electricity grid. Left: organizational level. Right: system (or cross-organizational) level. Adapted from [162].

On the other hand, the fact that most innovation happens at the boundaries between disciplines or specializations [87] also explains why innovation proves so difficult to create and maintain. *Conceptual* gaps exist between stakeholders from different practices. These gaps lead to multiple and often differing viewpoints that can be hard to incorporate in a fair and flexible manner. In addition, and contrary to the "myth of unidisciplinary competence" [15], conceptual gaps also exist within a particular practice. These are gaps between members focusing on specialties that are only very remotely related, or gaps between members with different levels of competence –experts and novices.

Other barriers to cooperation include *spatial* and *temporal* distances that limit cooperative efforts between different communities [43]. The various stakeholders concerned with the future of the U.S. electricity grid are spatially distributed across the country with limited opportunities to meet face-to-face. Even though communication technology enables new forms of collaborative work, critical stages of collaborative work –such as dealing with "ill-defined" problems– appear to require some level of face-to-face interaction [117].

Temporal distances relate to the fact that complex systems such as the electricity grid are not designed once and for all. Instead, their initial design is followed by extended periods of evolution and redesign involving people who were not members of the original design team [43]. This is particularly relevant to the electricity industry, with the first electric networks being built a century ago: the majority of the current transmission and distribution lines are 25 years or older; many of the energy management systems currently in use were installed in the 1970s and coded in FORTRAN –a programming language originally developed in the 1950s; and the original specifications of existing hardware and software are often missing. In addition, the workforce is aging: 25 to 35% of the utility technical workforce as of 2010 is likely to retire by 2015 [97], which will create additional temporal gaps between and within organizations and communities concerned with the electricity grid.

Finally, cultural differences between groups may also constitute a barrier to cooperation. In particular, climate change and energy security –two issues that the emerging electricity grid aims to tackle– are inherently international issues to which national solutions can at best offer partial answers [161]. These issues require some form of international cooperation between national organizations, or within international teams. Differences in process or values increase the likelihood of misunderstandings [66, 67].

Thus, we argue that the spatial, temporal, conceptual and cultural distances between the various communities-of-practice involved in the modernization of the electricity grid constitute obstacles preventing effective cooperation. We claim that a reduction of these distances constitutes an instrumental goal that would tremendously increase the prospects for convergence towards a shared vision for the future electricity grid.

Market forces alone cannot tackle this goal due to valuation and free-riding problems arising from the public good nature of any shared architecture. Traditional planning methods focused on computing optimal solutions are equally ineffective at addressing this goal due to the ill-defined nature of the grid architecture problem. There is no optimal solution to the architecture problem that would be substantively rational. Instead, the rationality of good solutions to the architecture problem (i.e. good architecture models) will be predominately a procedural rationality. In the rest of this chapter, we therefore attempt to develop an "effective procedural technique" [137] to address the grid architecture problem, drawing on the concepts of broker, boundary object, and boundary organization. Secondly, we examine what role policymakers could play to facilitate this process.

4.4 Theoretical framework

In this section, we introduce the notions of *brokers* [162] and *boundary objects* [140] that have been proposed as possible channels through which distinct communities can communicate and cooperate (Fig. 4.3). The rest of this chapter will draw on this theoretical framework.

4.4.1 Brokers

Brokering consists of connections provided by people who can introduce elements of one community into another [162]. Brokering often arises from multi-membership: a member of several communities can potentially help translate, coordinate, and align their various perspectives. A broker is not a manager who simply coordinates multiple specialists; he is an individual who has knowledge in multiple specialties. In the literature, the terms boundary analyst [46], organizational translator [12], and boundary spanner [85, 105] are also used to refer to those individuals who can frame the interests of one community in terms of other communities' perspectives.

In the energy sector, the emerging need for brokers results mechanically from the inevitable transition towards an energy system transcending traditional disciplines. This transition requires the electricity industry to move beyond the standard approach where engineers solve technical problems, policymakers craft legislation, economists analyze what motivates personal energy choices, political scientists focus on the governance of the grid, biologists discuss environmental impacts, communication majors translate complex language, and sociologists develop tools to influence behavior [84].

The electricity industry has recognized the need for "super-engineers" able to work simultaneously in multiple domains such as power systems, information science and digital technology [122]. Fisher and Schoenberger argue that engineers can bring a technological awareness to the policy debate and, reciprocally, they should also be able to identify and re-think their own technical assumptions, particularly during times of economic and regulatory change [44]. Kirshenbaum and Webber advocate for experts equipped to navigate through all of the technical, political and social issues related to energy [84].

The rise of this nascent labor force with new competencies in the area of energy and sustainability requires planning educational programs, developing cross-disciplinary curricula, and assessing existing programs accordingly [6]. Current students must typically choose to enroll in a single department where they are exposed to narrow perspectives of the energy sector and do not obtain comprehensive understanding of what lies ahead [84]. Barriers to these developments include the lack of recognition for cross-disciplinary education and experience, and more generally the difficulty to evaluate cross-disciplinary research going beyond a specific field of study [110].

It is notable that none of the planning reports or roadmaps that we reviewed identified the necessity of major, cross-disciplinary evolutions in academic curricula. The need to rejuvenate the U.S. power and energy workforce is often recognized, but the need to facilitate the rise of brokers to establish new connections between the growing number of communities-of-practice involved is never mentioned, nor is the transdisciplinary nature of the grid ever considered as a barrier to the modernization of the electricity grid.

4.4.2 Boundary objects

Boundary objects constitute a second option to build bridges across communities and a method of addressing ill-defined problems such as the grid architecture problem. Star and Griesemer [140] introduced the term boundary object to describe objects that are "both plastic enough to be adaptable across multiple viewpoints, yet robust enough to maintain a common identity" across more than one social world. Boundary objects have different meanings in different communities, but their structure is common enough to coordinate these different perspectives towards a shared purpose.

In practice, boundary objects consist of "artifacts, documents, terms, concepts, and other forms of reification around which communities of practice can organize their interconnections" [162]. Examples of boundary objects include maps [140], engineering design drawings [62], and timelines [167]. The concept of boundary object has been utilized across a range of fields including new product development [17], project management [132], biomedical innovation [142] and educational policy [36]. In this chapter, we propose to *consider architecture models* for the future electricity grid *as boundary objects*.

The initial framing of the concept of boundary object was motivated by the desire to analyze the nature of cooperative work in the absence of consensus [140]. In this context, boundary objects are essentially working arrangements addressing information and work requirements as perceived by various groups who wish to cooperate. They are organic structures that arise over time from durable cooperation among communities-of-practice and help develop and maintain coherence between them [10].

"Interpretive flexibility" is at the core of boundary objects and consists of the possibility for different people to interpret and use differently the same object according to their local needs. Another salient characteristic is the dynamic between the high-level –and sometimes fairly vague– description of an object serving all the perspectives at once, and the more specific features tailored locally to the needs of each community [139].

The notions of brokers and boundary objects serve as theoretical framework for the approach that we propose to address the grid architecture problem. Brokers experience the gaps between the communities of which they are members as cognitive dissonances; they develop strategies to reduce them 'internally'. Boundary objects –and more specifically, the back-and-forth motions between their high-level and tailored descriptions—allow each community to (1) contrast the facts and norms that constitute their "boundary judgments" [150] with those of other communities (i.e.'externally'), (2) explore their implications, and eventually (3) revise them when necessary.

4.5 Small-scale experiment and discussion

In this section, we take an ethnographic approach and describe how boundary objects emerged within a cross-disciplinary team conducting research on electricity systems. We report on both the process that led to the production of boundary objects, and the boundary objects produced per se. This small-scale example illustrates how the theoretical framework introduced above can foster durable cooperation among communities-of-practice concerned with the future electricity grid, and develop and maintain coherence between them.

4.5.1 Anomalies and negotiation process

The Advanced Computational Electricity Systems (ACES) Laboratory at Georgia Tech is a cross-disciplinary research group of twenty members created in 2009. The group focuses on electricity systems for both small- and large-scale grids. A distinctive feature is that every group member has background in at least two disciplines, including power systems engineering, computer science, controls, communications, optimization, economics, finance, business administration, and public policy. Another feature is the cultural diversity within the group, with eight nationalities represented.

As they were starting to get involved into research projects related to the future electricity grid, ACES members rapidly faced barriers similar to some of the "anomalies" that Star identified as a basis for the emergence of boundary objects [139]. A number of elements or desired properties of the future electricity grid –such as the energy storage function—did not fit into the four-category representation of the grid, making it increasingly difficult to accurately describe the future state of the system using traditional representation models. Since some of the research that was being performed addressed realities that were not depicted in the traditional representation, reporting externally about this "backstage" work and putting it in perspective with the rest of the electricity system was problematic. Internally, these gaps also uncovered the difficulty to collect, organize, and coordinate distributed knowledge related to the ongoing projects among the researchers involved using traditional representations.

The need for new arrangements that would support the new information requirements of the future grid was addressed through a series of informal meetings that took place biweekly for about a year. These meetings provided opportunities for the group members to enter an informal process of negotiation to find new ways to describe the electricity grid. This negotiation involved the interaction of two constituent –and concurrent– processes, participation and reification ([162], Fig. 4.3). Group members participated in the process by bringing their vision of what the future grid was to look like in terms of objectives, properties, and requirements based on their own understanding of the desired grid properties. At the same time, symbols, concepts, diagrams and use cases that congealed some aspects of the discussion were being produced. This dual process of reification created points of focus around which the discussion became organized. Some of these reified aspects would later be modified again to repair misalignments or incoherence.

As the discussion was moving forward, each participant was going back-and-forth between the high-level description of the grid that was emerging out of these meetings, and some local aspects of the grid that he or she was more specifically working on. This dynamic between the ill-structured frame that all participants were developing in common, and the local use of this frame in individual research projects, was a way to identify and correct inconsistencies.

4.5.2 Emergence of the energy prosumer as a boundary object

The concept of energy prosumer emerged as the main point of focus around which the discussion became organized. The word prosumer is a portmanteau formed by contracting the word producer with the word consumer. In the literature, the concept of prosumer has been mainly used as an abstract concept merging the economic functions of consumers and producers [147, 143, 144, 145, 125]. In the context of the ACES group, the energy prosumer emerged organically from the discussions as an undifferentiated entity performing multiple energy functions, contrary to the four traditional categories limited to perform one single function. The name prosumer came from the observation that an increasing number of grid actors –in particular the electricity end-users– were to consume, but also produce electricity moving forward. Later in the discussion, the prosumer object was also equipped with two additional functions, the ability to store, and the ability to transport electricity.

The prosumer object is both conceptual and material. It is at the same time an abstract representation of a class of electricity grid components, a cyber-physical system that can monitor and manage generation, consumption, storage, and transmission assets owned and controlled by a prosumer owner, and a decision-making entity that has objectives associated with the control and utilization of electricity. These objectives are aligned with the goals of the prosumer owner –individual or organization– and relate to preferences expressed in terms of economic value, efficiency, security, comfort and/or sustainability.

A fundamental property of the prosumer object is that virtually every component of the electricity grid can be represented as a prosumer, across any scale of space (spatial occupation) or time (lifetime) as shown in Fig. 4.4. A home, a building, a power transformer are all prosumers. A utility grid, a microgrid, and a laptop computer can also be represented as prosumers.

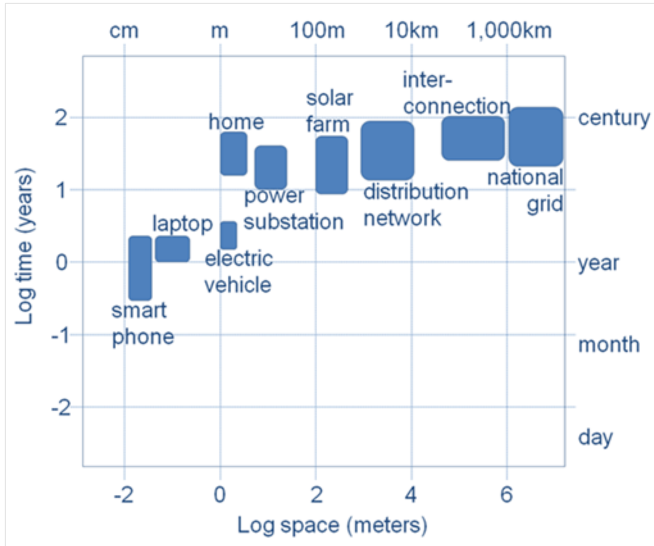


Figure 4.4: Representation of energy prosumers at various scales of time and space.

Other properties of the energy prosumer include typical characteristics of boundary objects [162]:

1. Modularity: each community of practice concerned with the future electricity grid can relate its activities to at least one specific portion of the prosumer. Technology vendors implement systems that enable the prosumer functions; economists analyze what motivates the goal of the prosumer owner; policymakers craft legislation to regulate the prosumer functions, etc.

2. Abstraction: all perspectives are served at once by deletion of features that are specific to each perspective. For example, an electric vehicle can be seen as an energy prosumer by deleting all its specific features such as its ability to move individuals and goods in space and time.

3. Accommodation: each community of practice can accommodate the prosumer to its own activities, developing specific features tailored to their local needs when needed. For example, specific energy scheduling algorithms can be developed for residential prosumers [70].

4. Standardization: the information contained in a boundary object is in pre-specified form so that each community of practice knows how to deal with it locally. In the case of the energy prosumer, the information is organized into an objective or utility function, and four energy functions: produce, transport, consume, and store.

4.5.3 Towards a boundary infrastructure for the future electricity grid

The energy prosumer, as a cyber-physical system, is not isolated: it exchanges energy and information with other prosumers. The concept of energy services emerged from the discussions to refer to these exchanges that take place through either bilateral contracts or market actions. Each type of energy service is to include particular specifications based on the desired performance of the service and the objectives it intends to meet. At the same time, some features are likely to be common to every energy service: price, time of delivery, identity of the buyer and seller, etc. Thus, energy services are also boundary objects whose exact meaning and characteristics in the context of the future electricity grid are to be negotiated.

Prosumers and energy services are two classes of boundary objects that can be used to represent both the elements and interfaces that constitute the electricity grid. The current, hierarchical organization of the grid can be described as nested, with higher levels consisting of, and containing, lower levels (Fig. 4.5, left). The national electricity grid consists of, and contains all the large interconnections. Each interconnection consists of, and contains various transmission and distribution networks. These entities contain not only a network, but also the various customers they serve. Similarly, each home grid consists of the multiple electric devices it contains: computers, light bulbs, appliances, etc. All of these entities can also be modeled as energy prosumers and their interactions as energy services (Fig. 4.5, right), giving birth to a new, flat representation of the electricity grid. At the prosumer level, prosumer owners pursue their own objectives while at the system level, experts and elected officials set objectives for the entire grid.

The concepts of rules and mechanisms defined in hierarchy theory [4] can be used to characterize the dynamics of the structure obtained. At the system level, rules are set for the common good. These rules constrain both the way energy prosumers buy and sell energy services externally, and the way their internal functions –consume, produce, store and transport electricity– are implemented. At the prosumer level, prosumer owners set mechanisms that allow them to pursue their objectives within the rules set at the system level. These mechanisms can take the form of hardware and/or software technology enabling one or several of the four functions. Both the rules set at the system level and the mechanisms set at the prosumer level are boundary objects whose meaning and characteristics are to be negotiated.

The electricity grid can therefore be modeled as a system of boundary objects interacting with each other: energy prosumers, energy services, rules and mechanisms. Bowker and Star [10] introduce the concept of *boundary infrastructure* to refer to such objects that cross larger levels of scale than boundary objects. A boundary infrastructure is a cross-contextual information system that serves multiple communities-of-practice simultaneously, be these within a single organization, or distributed across multiple organization as is the case with the electricity grid (Fig. 4.3). Any given community of practice can interface with the infrastructure, pull out the kinds of information objects it needs, and tailor some of these objects to the local needs.

4.5.4 Discussion

4.5.4.1 Implications of the ACES example: Process observed, objects created, scale limitations

Though small in scale, the ACES example provides valuable insights on the use of brokers and boundary objects to foster cooperation among communities-of-practice concerned with the future electricity grid.

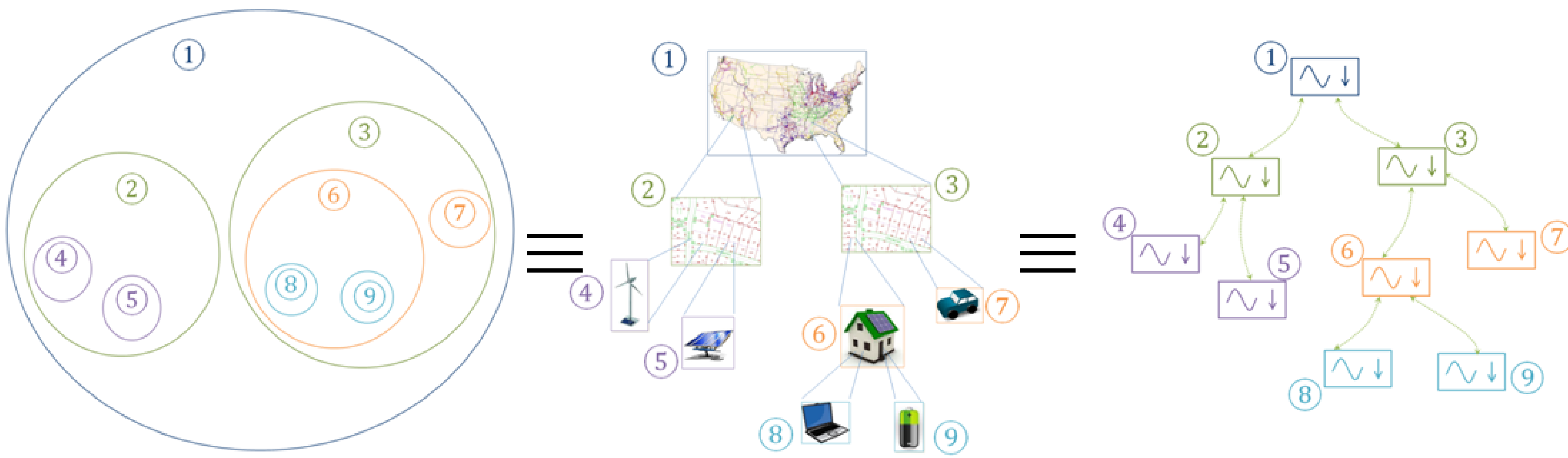


Figure 4.5: Representation of the electricity grid as a nested hierarchy (left), and as flat structure consisting of prosumers interacting with each other (right).

The boundary infrastructure jointly produced through discussion and negotiation is a model of form representing both the elements and interfaces that constitute the electricity grid; it helped reduce the distances between the different communities-of-practice represented within the group, be these conceptual (multiple disciplines represented), temporal (new members regularly joining and others leaving the group) or cultural (multiple nationalities and cultural backgrounds); it served as an information structure across context and facilitated the establishment of several trans-disciplinary research projects related to the future electricity grid.

Through back-and-forth movements between the common and tailored forms of the boundary infrastructure that was being produced, each member participated in defining a shared vision of the whole system and developed specific features at some local levels with the common structure in mind. This suggests that the development, negotiation and use of boundary objects can help reduce the distortions in objectives, models and implementations that inevitably arise between the local and system standpoints.

A fundamental contribution of the boundary infrastructure produced is its flexibility over time. Contrary to the rigid representation of the grid currently in use, the boundary infrastructure developed –and in particular the concept of prosumer—can be used to model any grid component in today's and tomorrow's electricity grid, when grid entities gain access to additional energy functions and services. The boundary infrastructure proposed can therefore support the development of timelines [167] showing multiple dimensions of change and multiple states –or "stable intermediate forms" [93]—of the same system, but using the same representation.

The various communities represented within the ACES laboratory were able to self-manage their interactions and the objects they produced. Could this approach be extended at a larger scale, with a much larger number of actors and communities?

Practically speaking, how can these various communities –with different concerns, languages, forms of interaction, and practices—succeed in establishing and maintaining cooperation? And how can their actions –and the boundary objects they produce– be managed in practice? We address these questions in section 4.6 through the concept of boundary organization.

4.5.4.2 Boundary objects vs. standardization: Differences in the context of the electricity grid

Standards and boundary objects are interrelated concepts: both standards and boundary objects arise over time from durable cooperation among communities [10], and the term *boundary object* was initially introduced as one of two major factors that contributed to the successful cooperation between biologists and amateur naturalists, along with *methods standardization* [140].

While Star and Griesemer found methods standardization to be necessary, they did not find it sufficient to enable the type of cross-contextual cooperation that is needed today to support the development of a vision for the future electricity grid. The processual nature of the informational space –in particular the back-and-forth movements between common and local descriptions– and the fact that both people and information objects inhabit multiple contexts require a "richer vocabulary than that of standardization or formalization" [10], namely the use of boundary objects.

The concept of *naturalization* characterizes the difference between standardization and boundary objects. A community of practice is defined in large part according to the co-use of objects –tools, artifacts, techniques, ideas, etc.– that mediate its action. These objects exist, with respect to a community, along a trajectory of naturalization. The degree of naturalization of an object evolves over time as a "measure of taken-for-grantedness": the more naturalized the object becomes, the more it loses its "anthropological strangeness". Boundary objects such as the energy prosumer are working arrangements that both arise from, and resolve the differences of naturalization that inevitably occur between communities. They do so without imposing across the board a naturalization of categories from one community in particular, or from an outside source of standardization [10]. Over time, boundary objects tend to evolve into standardized objects: their ill-structured (common) and well-structured (local) aspects progressively become equivalent and the same objects become naturalized in several communities. New residual categories are then generated from which new boundary objects can rise [139].

In the U.S., the technology-centered approach of the past decade put a strong emphasis on technology standardization through the development of smart grid interoperability standards. The EISA of 2007 directed the National Institute of Standards and Technology (NIST) to "coordinate the development of a framework that includes protocols and model standards for information management to achieve interoperability of smart grid devices and systems"; the GridWise Architecture Council identified areas where standardization were needed to allow technical, information and organizational interoperability [146]; finally, the IEEE Standards Association published a draft guide for smart grid interoperability [74].

Technology standardization is important and should continue to receive attention. But the successful development of a vision for the future grid requires expanding both the scope of action –moving from a technology-focused approach to a more holistic approach integrating system architecture considerations– and the means of action –encouraging the use of brokers and boundary objects. Considering the architecture of the future electricity grid as a *system of boundary objects* will foster cooperation across contexts and help establish consensus across communities. Once one particular reference architecture –that is, a template solution for an architecture– becomes naturalized in a sufficient number of communities and implementations of this reference architecture have been proposed and tested, it will progressively become standard within and across the multiple worlds in which it is naturalized.

4.6 Scaling-up: A boundary organization in charge of developing architecture models

We initially approached the grid architecture problem in two ways: as an ill-defined problem, and as a market failure. After reframing the problem in term of communities-of-practice, we introduced the concepts of brokers and boundary objects as tools that could be used to build bridges between these communities and facilitate cooperation. As illustrated in the ACES case, brokers and boundary objects can be proposed as non-conventional means to address the ill-defined nature of the problem. In this section, we now turn to the market failure aspects of the problem, and the need for a scalable approach, possibly up to the national level.

4.6.1 Form of government intervention

It is widely accepted that the transition process towards a smarter electricity grid requires at least some level of government oversight. This is due in part to the communal nature of the electricity grid and its direct impact on the economy and national security. More specifically, it has been recognized that "national leadership is needed to create a shared vision of the future [of the electricity grid]" (emphasis added) [30].

The fact that no system architecture has emerged in the literature after ten years of prevailing technology-oriented programs serves as ex-post evidence that markets alone cannot converge to an architecture for the future grid in the desired time frame. This ex-post evidence adds to our previous ex-ante analysis focusing on externalities and public good aspects. While government should let markets drive the architecture implementation, there is a need for some public intervention to expedite the development of architecture models for the future national grid.

What form of intervention is appropriate, and how public leadership should be articulated? In the rest of this section, we propose to address the need for public intervention through the creation of a boundary organization in charge of developing architecture models for the future U.S. grid.

4.6.2 Boundary organizations

Boundary organizations provide an institutionalized space "between politics and science" [60] where multiple communities participate in the "co-production" [78] of knowledge and social order. In the context of boundary organizations, the term "politics" is used in its broadest definition to include policy, legislative, management, and resource allocation decisions, and the term "science" refers broadly to any learning process that builds and organizes knowledge in a systematic way.

Boundary organizations theory has been developed in a variety of science-policy contexts including climate [2, 21, 100], health [60, 82], agriculture [19, 20], and water [164]. The theory draws on the notion of boundary work –the negotiation of social boundaries between what is 'politics' and what is 'science' [52, 53]– and on the idea that blurring these boundaries can lead to more productive policy making [76, 79].

Guston suggested three criteria to characterize boundary organizations: (1) they provide the opportunity and sometimes the incentives for the creation and use of boundary objects; (2) they involve the participation of actors from both sides of the boundary as well as professionals who serve a mediating role; (3) they are distinctly accountable to both political and scientific institutions [60, 61]. Cash also suggested that boundary organizations (a) serve to frame and define the scale of problems, (b) mediate information flows, and (c) capitalize on advantages of scale [20].

Because of their dual accountability, boundary organizations provide an opportunity for the stabilization and negotiation of the boundary space between science and politics. From a principal-agent perspective, boundary organizations are agents accountable and responsive to both scientific and political principals. This need to respond to several principals prescribes a balanced and stable approach to the organization's mission [61].

Despite being a relatively new concept in policy-making circles, boundary organizations can be proposed as an institutionalized form adapted to the co-production of architecture models for the future electricity grid between the various communities involved.

4.6.3 The Smart Grid Interoperability Panel (SGIP): a boundary organization?

Over the past decade, the SGIP has probably been the only organization in the U.S. to make tangible, publicly-available contributions towards the development of architecture models for the future electricity grid. We propose to analyze and compare the SGIP's mission and structure to Guston's criteria for characterizing boundary organizations.

The SGIP was established by NIST in late 2009 as a public-private partnership to support its responsibility under the EISA of 2007 to coordinate standards development for the Smart Grid. As of April 2012, the SGIP was comprised of over 750 member organizations representing 22 stakeholder categories, with more than 2,000 individuals participating in SGIP activities. As of January 2013, the SGIP transitioned to "SGIP 2.0", a self-sustaining, legal entity that retains a working partnership with NIST [116].

The SGIP has three primary functions: (1) to oversee activities intended to expedite the development of interoperability and cyber security specifications within standards-setting organizations; (2) to provide technical guidance to facilitate the development of standards for a secure, interoperable smart grid; and (3) to specify testing and certification requirements necessary to assess the interoperability of smart grid-related equipment [114].

The SGIP, through its Smart Grid Architecture Committee (SGAC), has also developed a "reference model", that is "a set of views (diagrams) and descriptions that are the basis for discussing the characteristics, uses, behavior, interfaces, requirements, and standards of the Smart Grid" [115]. This model essentially extends the traditional representation of the electricity grid by building additional categories on top of the four traditional categories (Fig. 4.2).

Three fundamental factors have greatly limited the SGIP's efforts on developing shared architecture models for the future grid: its focus on interoperability, a limited involvement of policymakers, and the absence of dual accountability. First, the SGIP has been mainly focused on interoperability since its creation, considering the development of architecture models only as a means to enable smart grid interoperability (cf. section II-D-4). Second, policymakers were only remotely involved in the SGIP's activities. Since its creation, the SGIP participated in the creation and use of boundary objects related to the future architecture of the grid –although they were not referred to as such– including its "reference model". However, the various actors participating in the elaboration and negotiation of these objects were predominantly coming from the scientific side of the boundary. NIST also provided human resources to assist with technical and operational aspects of the work, but these resources were primarily scientific experts, not policymakers. Third, because of the disconnect between the SGIP's main objective –to enable interoperability– and the broader policy objectives for the future grid, the SGIP has never been responsible and accountable to the policy side of the boundary, in particular regarding its activities related to the development of an architecture for the future grid. The fact that SGIP 2.0 is now legally and financially independent from NIST does not prefigure a change in that matter.

Therefore, despite its significant and valuable efforts to compile existing smart grid standards and identify and address standards gaps, the current structure of the SGIP does not meet the criteria defining boundary organizations because of a limited involvement of policymakers and the absence of dual accountability (Table 4.3).

Table 4.3: Comparison between Guston's criteria for boundary organizations and NIST SGIP

	(1) Creation and use of boundary objects	(2) Participation of actors from both sides of the boundary	(3) Dual accountability to science and policy communities
Boundary organization	●	●	●
NIST SGIP	●	◗	❍

4.6.4 Needed: a boundary organization in charge of designing architecture models for the future electricity grid

The concept of boundary organizations can be proposed as an institutionalized form adapted to the co-production of architecture models for the future electricity grid between science and policy actors. In particular, actors coming from the policy side should not be limited to technical advisors –as with the SGIP—but also include policymakers, and the organization should have distinct lines of responsibility and accountability to both political and scientific worlds.

The creation and operation of such boundary organization dedicated to the future grid architecture would change the current situation where architecture development is subordinated to grid interoperability and replace architecture development at the top of the pyramid. This organization could also go beyond the science-policy dimension to incorporate levels of organization, from the local to the state and the national level, and link science and policy across different levels [20]. The U.S. energy policy is notoriously suffering from inconsistent policies across different levels of scales, and such organization would ensure architecture consistency across scales.

4.7 Conclusion: findings and recommentations

The development of new architecture models for the future electricity grid is necessary in response to three challenges. First, the future electricity grid will lack a central management authority, but shall continue to perform some centrally agreed-upon purposes in a collaborative manner. Thus, new architecture models are needed to guide future evolutions through stable intermediate forms, and serve as a structure around which future collaboration can take place. Second, the blurring of knowledge boundaries between the various disciplines concerned with the grid has created the need for a new ontology that transcends these boundaries. Thus, new architecture models are needed to create a common universe of discourse between the discussants involved in grid modernization efforts. Third, the traditional, four-category representation of the grid is too rigid to accurately describe the emerging functions of the grid. Thus, new architecture models are needed to accommodate for the new storage function and the emerging decision-making entities performing multiple functions.

Although the need for new architecture models has been identified in some circles, the recent efforts to address this need have been undermined by confusions in terminology, the persistence of legacy representations, and the predominance of interoperability considerations. These difficulties also relate to the very nature of the problem. The grid architecture problem –namely the absence of architecture— can be framed as both a market failure –legitimizing government intervention– and an ill-defined problem –requiring the development of non-conventional methods of solution. The substantive problem can be conceptualized as distances –spatial, temporal, conceptual and cultural– that prevent the various communities-of-practice involved to effectively cooperate.

The concepts of brokers and boundary objects can be proposed to address the ill-defined nature of the grid architecture problem. Brokers experience the gaps –and in particular the conceptual gaps—between the communities of which they are members as cognitive dissonances; they develop strategies to reduce these gaps 'internally'. Boundary objects allow multiple communities-of-practice to confront and contrast 'externally' the facts and norms conditioning their problem definition or solution.

We illustrated on a small-scale example how architecture models considered as boundary objects could be developed in the presence of brokers. The concept of boundary organizations can be proposed as an institutionalized form adapted to scale-up this approach. We showed that the SGIP –the only prominent organization in the U.S. to make tangible, publicly-available contributions towards the development of grid architecture models over the past decade—was lacking some of the characteristics of a boundary organization.

Based on these findings, we formulate the following policy recommendations to expedite the development of architecture models for the future electricity grid:

1. Formally recognize the necessity to develop architecture models for the electricity grid of the future, and acknowledge the need for public intervention due to the incapacity of markets to supply such models.

2. Encourage major, cross-disciplinary evolutions in academic curricula that support the emergence of a new type of electricity grid professionals with knowledge in multiple specialties, and facilitate the creation of trans-disciplinary research programs on electricity grid.

3. Create a boundary organization specifically in charge of developing architecture models for the future electricity grid. This organization should involve the participation of actors from both sides of the boundary (science and policy) as well as brokers serving as mediators

4. Support the active participation of policymakers in the boundary organization as policy principals, along with science principals, to ensure dual accountability is maintained.

4.8 Appendix

Table 4.4: Individuals or organizations likely to affect or be affected by the future electricity grid in the U.S.

Group	Members
Electricity end-users	Residential, Commercial, Industrial, Government including the Military.
Grid elements vendors	Companies involved in the design, manufacturing, distribution, installation, maintenance and dismantling of the elements (hardware and software) constituting the grid as a cyber-physical system, at any scale (from semiconductors to transformers, solar cells, lines, control algorithms, communication systems, etc.).
Electric devices vendors	Companies involved in the design, manufacturing, distribution, installation, maintenance and dismantling of devices taking electricity in input and delivering a direct service to human beings in output (Ex: appliances, light bulbs, cars, electric train/tram/metro, etc.).
Testing and certification vendors	Organization which issue test certificates or manufacture equipment used either for pre-testing or during the conformance testing process.
Standards and specification development organizations	Organizations that create national or international standards specifications through an open, public process.
Rentier states	Countries/states/regions deriving a substantial portion of their revenues from selling their fuel resources to U.S. customers (coal, uranium, gas, petroleum, etc.).
Fuel-related companies	Companies involved in the extraction, transportation, transformation, and distribution of fuels for electricity generation and/or transportation: coal, uranium, natural gas, fuel oil and biofuels.

Vertically-integrated power providers	Investor-owned utilities; Municipal utilities and public utility districts; Rural electric co-ops; Federal power agencies; Public power agencies; Power pools.
Pure plays, generation segment	Transmission owners; Transmission companies; ISOs/RTOs; Utility distribution companies.
Pure plays, transmission and distribution segment	Transmission owners; Transmission companies; ISOs/RTOs; Utility distribution companies.
Entities active in the electricity delivery without owning physical assets	Electric marketers; Financial service companies.
Regulatory bodies	Federal level: FERC, NIST, EPA, NERC; State level: States commissions; local level: local governments for Municipals, co-op boards for rural electric co-ops.
Government bodies	Federal level: DOE, DOD, DOT, DHS, DOC, DOL (executive) and Congress (legislative); State level (executive and legislative).
Research organizations (not part of a company)	National labs, Universities/academia, Independent research institutes.
Entities investing in organizations concerned with the future grid	From venture capitalists investing in startup companies to private investors, banks, and donors supporting an advocacy group.
Advocacy groups	Groups advocating on behalf of an organization or a group of organizations (e.g. coal industry, utility industry, wind turbine industry, consumers, etc.). Groups advocating for a specific goal/objective that relates to the grid (e.g. sustainability, energy security, etc.).

Education bodies	Universities (initial education) as well as professional organizations (continuing education) that train and educate individuals in fields that relate to the grid (engineering, policy, environment, finance, etc.).
Support services companies	Any company providing support services to any of the actors listed above (legal, accountancy, consultancy, etc,).

REFERENCES

[1] Abbott, M., "Is the security of electricity supply a public good?," *The Electricity Journal*, vol. 14, pp. 31 – 33, 2001.

[2] Agrawala, S., Broad, K., and Guston, D. H., "Integrating climate forecasts and societal decision making: challenges to an emergent boundary organization," *Science, Technology, and Human Values*, no. 4, p. 454, 2001.

[3] Ahuja, R. K. and Orlin, J. B., "Inverse optimization," *Operations Research*, vol. 49, no. 5, pp. 771–783, 2001.

[4] Allen, T. F. H. and Starr, T. B., *Hierarchy : Perspectives for ecological complexity.* University of Chicago Press, 1982.

[5] Anghelita, P., Chefneux, M., Balaban, R., and Trocan, L., "Energy storage systems for buildings equipped with photovoltaic cells," in *3rd Int. Symp. Electr. Electron. Eng. (ISEEE)*, pp. 332–335, 2010.

[6] Batterman, S., Martins, A., Antunes, C., Freire, F., and Gameiro da Silva, M., "Development and application of competencies for graduate programs in energy and sustainability.," *Journal of Professional Issues in Engineering Education and Practice*, vol. 137, no. 4, pp. 198 – 207, 2011.

[7] Bieberstein, N., *Service-oriented architecture compass : business value, planning, and enterprise roadmap.* IBM Press, 2006.

[8] Bohn, R. E., S. J. E., "How much information? A 2009 report on american consumers," 2009.

[9] Borbely, J.-M. and Kredier, J. F., *Distributed generation–The power paradigm of the new millennium.* CRC, 2001.

[10] Bowker, G. C. and Star, S. L., *Sorting things out: Classification and its consequences.* MIT Press, 1999.

[11] BPC, "Policies for a modern and reliable US Electric grid," 2013.

[12] Brown, J. S. and Duguid, P., "Structure and spontaneity: Knowledge and organization," in *Managing industrial knowledge* (Nonaka, I. and Teece, D., eds.), London: Sage Publications, 2001.

[13] Buchanan, J. M., *The demand and supply of public goods.* Chicago: Rand McNally, 1968.

[14] California Public Utilities Commission (CPUC), "CPUC adopts rules to protect the privacy and security of customer electricity usage data," in *Press release, Jul. 28, 2011.*

[15] Campbell, D. T., "Ethnocentrism of disciplines and the fish-scale model of omniscience," in *Interdisciplinary collaboration: An emerging cognitive science* (Derry, S. J., Schunn, C. D., and Gernsbacher, M. A., eds.), London: Sage Publications, 2005.

[16] Campoccia, A., Dusonchet, L., Telaretti, E., and Zizzo, G., "Economic impact of ice thermal energy storage systems in residential buildings in presence of double-tariffs contracts for electricity.," in *6th Int. Conf. Eur. Energy Market (EEM)*, 2009.

[17] Carlile, P. R., "A pragmatic view of knowledge and boundaries: Boundary objects in new product development," *Organization Science*, no. 4, pp. 442–455, 2002.

[18] Carlile, P. R., "Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries.," *Organization Science*, no. 5, pp. 555–568, 2004.

[19] Carr, A. and Wilkinson, R., "Beyond participation: Boundary organizations as a new space for farmers and scientists to interact," *Society and Natural Resources*, vol. 18, no. 3, pp. 255 – 265, 2005.

[20] Cash, D. W., "'in order to aid in diffusing useful and practical information': Agricultural extension and boundary organizations.," *Science, Technology, and Human Values*, no. 4, p. 431, 2001.

[21] Cash, D. W. and Moser, S. C., "Linking global and local scales: Designing dynamic assessment and management processes," *Global Environmental Change*, vol. 10, pp. 109 – 120, 2000.

[22] CEN-CENELEC-ETSI Smart Grid Coordination Group, "Smart grid reference architecture," 2012.

[23] Chen, C., Kishore, S., and Snyder, L., "An innovative rtp-based residential power scheduling scheme for smart grids," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 5956–5959, May 2011.

[24] Chen, J., Yang, B., and Guan, X., "Optimal demand response scheduling with stackelberg game approach under load uncertainty for smart grid," in *IEEE Third International Conference on Smart Grid Communications (SmartGridComm)*, pp. 546–551, 2012.

[25] Chen, X., Wei, T., and Hu, S., "Uncertainty-aware household appliance scheduling considering dynamic electricity pricing in smart home," *Smart Grid, IEEE Transactions on*, vol. 4, no. 2, pp. 932–941, 2013.

[26] Chen, Z., Wu, L., and Fu, Y., "Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1822–1831, 2012.

[27] Choi, B. C. K. and Pak, A. W. P., "Multidisciplinarity, interdisciplinarity and transdisciplinarity in health research, services, education and policy: 1. definitions, objectives, and evidence of effectiveness," *Clinical and Investigative Medicine.*, vol. 29, no. 6, pp. 351 – 364, 2006.

[28] Conejo, A., Morales, J., and Baringo, L., "Real-time demand response model," *IEEE Transactions on Smart Grid*, vol. 1, no. 3, pp. 236–242, 2010.

[29] Depuru, S., Wang, L., Devabhaktuni, V., and Gudi, N., "Smart meters for power grid–challenges, issues, advantages and status," in *IEEE/PES Power Systems Conference and Exposition (PSCE)*, pp. 1–7, 2011.

[30] DOE, "'Grid 2030': A national vision for electricitys second 100 years," 2003.

[31] DOE, "National electric delivery technologies roadmap," 2003.

[32] Dong, M., Meira, P., Xu, W., and Chung, C., "Non-intrusive signature extraction for major residential loads," *IEEE Transactions on Smart Grid*, vol. 4, no. 3, pp. 1421–1430, 2013.

[33] Dunn, B., Kamath, H., and Tarascon, J.-M., "Electrical energy storage for the grid: A battery of choices," *Science*, 2012.

[34] Dunn, W. N., *Public policy analysis: An introduction.* 4th ed: Pearson, 2007.

[35] Electric Power Research Institute, "Report to NIST on the smart grid interoperability standards roadmap," 2013.

[36] Emad, G. and Roth, W.

[37] EPRI, "EPRI-DOE handbook of energy storage for transmission and distribution applications," 2003.

[38] Fagerberg, J., Mowery, D. C., and Nelson, R. R., *The Oxford handbook of innovation.* New York : Oxford University Press, 2006.

[39] Faghih, A., Roozbehani, M., and Dahleh, M. A., "On the value and price-responsiveness of ramp-constrained storage," *Energy Conversion and Management*, vol. 76, pp. 472 – 482, 2013.

[40] Federal Energy Regulatory Commission (FERC), "A national assessment of demand response potential," 2009.

[41] Federal Energy Regulatory Commission (FERC), "National action plan on demand response," 2010.

[42] Fernando, A., Jos, O., and Jos, C., "Open standards and open source: enabling interoperability," *International Journal of Software Engineering and Applications*, no. 1, p. 1, 2011.

[43] Fischer, G., "Social creativity: Turning barriers into opportunities for collaborative design," in *8th Participatory Design Conference*, 2004.

[44] Fisher, E. B. and Schoenberger, E., "Who's driving the bus: The importance of interdisciplinary awareness on the road to sustainability," in *IEEE Energy 2030 Conference*, 2008.

[45] Fuchs, H. U., *The dynamics of heat*. Springer.

[46] Garraway, J., "Creating productive interactions between work and the academy," *Higher Education*, no. 3, pp. 447–464, 2006.

[47] Gatsis, N. and Giannakis, G., "Decomposition algorithms for market clearing with large-scale demand response," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 1976–1987, 2013.

[48] Gellings, C. W., C. J. H., *Demand side management: Concepts and methods*. Fairmont Press, 1993.

[49] Gide, A., *Les nourritures terrestres*. Mercure de France, 1897.

[50] Gide, A., *The fruits of the earth*. Alfred A. Knopf Inc., 1949.

[51] Giebel, G., B. R. K. G. D. M. D. C., "The state of the art in short-term prediction of wind power," 2011.

[52] Gieryn, T. F., "Boundary-work and the demarcation of science from non-science: Strains and interests in professional ideologies of scientists," *American Sociological Review*, no. 6, pp. 781–795, 1983.

[53] Gieryn, T. F., "Boundaries of science," in *Handbook of science and technology studies* (Jasanoff, S., Markle, G. E., Peterson, J. C., and Pinch, T., eds.), London: Sage Publications, 1994.

[54] Grijalva, S., Costley, M., and Ainsworth, N., "Prosumer-based control architecture for the future electricity grid," in *IEEE International Conference on Control Applications (CCA)*, pp. 43–48, 2011.

[55] Grijalva, S. and Tariq, M., "Prosumer-based smart grid architecture enables a flat, sustainable electricity industry," in *IEEE PES Innovative Smart Grid Technologies (ISGT)*, pp. 1–6, 2011.

[56] Guan, X., Xu, Z., and Jia, Q.-S., "Energy-efficient buildings facilitated by microgrid," *IEEE Transactions on Smart Grid*, vol. 1, no. 3, pp. 243–252, 2010.

[57] Gudi, N., Wang, L., Devabhaktuni, V., and Depuru, S., "Demand response simulation implementing heuristic optimization for home energy management," in *North American Power Symposium (NAPS)*, pp. 1–6, 2010.

[58] Guille, C. and Gross, G., "A conceptual framework for the vehicle-to-grid (v2g) implementation," *Energy Policy*, vol. 37, pp. 4379 – 4390, 2009.

[59] Gungor, V., Sahin, D., Kocak, T., Ergut, S., Buccella, C., Cecati, C., and Hancke, G., "Smart grid technologies: Communication technologies and standards," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 4, pp. 529 – 539, 2011.

[60] Guston, D. H., "Stabilizing the boundary between us politics and science: The role of the office of technology transfer as a boundary organization.," *Social Studies of Science*, no. 1, p. 87, 1999.

[61] Guston, D. H., "Boundary organizations in environmental policy and science: An introduction," *Science, Technology, and Human Values*, no. 4, p. 399, 2001.

[62] Henderson, K., *On line and on paper: visual representations, visual culture, and computer graphics in design engineering.* Cambridge, MA: MIT Press, 1999.

[63] Henderson, R. M. and Clark, K. B., "Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms," *Administrative Science Quarterly*, vol. 35, no. 1, pp. 9 – 30, 1990.

[64] Herter, K., "Residential implementation of critical-peak pricing of electricity," *Energy Policy*, vol. 35, pp. 2121–2130, 2007.

[65] Hledik, R., "How green is the smart grid?," *The Electricity Journal*, vol. 22, pp. 29 – 41, 2009.

[66] Hofstede, G., *Culture's consequences : international differences in work-related values.* SAGE Publication, 1980.

[67] Hofstede, G., *Cultures and organizations : software of the mind.* New York : McGraw-Hill, 1991.

[68] Hubert, T. and Grijalva, S., "Home energy manager: A consumer-oriented interactive tool to optimize energy use," in *IEEE International Conference on Consumer Electronics (ICCE)*, pp. 505–506, 2011.

[69] Hubert, T. and Grijalva, S., "Realizing smart grid benefits requires energy optimization algorithms at residential level," in *IEEE PES Innovative Smart Grid Technologies (ISGT)*, pp. 1–8, 2011.

[70] Hubert, T. and Grijalva, S., "Modeling for residential electricity optimization in dynamic pricing environments," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 2224–2231, 2012.

[71] HUGHES, T. P., *Networks of power. Electrification in western society, 1880-1930*. The Johns Hopkins University Press, 1983.

[72] IEEE, "Ieee standard computer dictionary: A compilation of ieee standard computer glossaries," 1991.

[73] IEEE, "Ieee standards glossary," 2010.

[74] IEEE, "Ieee draft guide for smart grid interoperability of energy technology and information technology operation with the electric power system (eps), and end-use applications and loads.," 2011.

[75] ILLINOIS STATEWIDE SMART GRID COLLABORATION (ISSGC), "Illinois statewide smart grid collaborative: Collaborative report," 2010.

[76] JASANOFF, S., *The fifth branch: Science advisors as policymakers*. Harvard University Press, 1990.

[77] JASANOFF, S., *The Medici Effect: Breakthrough Insights at the Intersection of Ideas, Concepts, and Cultures*. Harvard Business School Press Books, 2004.

[78] JASANOFF, S., *States of knowledge : The co-production of science and social order*. New York : Routledge, 2004.

[79] JASANOFF, S., "Is science socially constructed–and can it still inform public policy," *Science and Engineering Ethics*, vol. 2, no. 3, pp. 263 – 276, 1996.

[80] JIA, L. and TONG, L., "Day ahead dynamic pricing for demand response in dynamic environments," in *IEEE 52nd Annual Conference on Decision and Control (CDC),*, pp. 5608–5613, 2013.

[81] JOO, J.-Y. and ILIC, M., "Multi-layered optimization of demand resources using lagrange dual decomposition," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 2081–2088, 2013.

[82] KEATING, T. J., "Lessons from the recent history of the health effects institute," *Science, Technology, and Human Values*, no. 4, p. 409, 2001.

[83] KHURANA, H., HADLEY, M., NING, L., and FRINCKE, D., "Smart-grid security issues," *IEEE Security and Privacy*, vol. 8, no. 1, pp. 81 – 85, 2010.

[84] KIRSHENBAUM, S. R. and WEBBER, M. E., "Degree courses: Energy should form its own discipline," *Nature*, vol. 478, no. 7367, p. 37, 2011.

[85] KLEINMAN, D. L., *Politics on the endless frontier : postwar research policy in the United States*. Durham : Duke University Press, 1995.

[86] KRAHN, G., "Interdisciplinary culture–a result not a goal," in *Interdisciplinary Workshop on Core Mathematics: Considering Changes in the First Two Years of Undergraduate Mathematics*, 1999.

[87] Leonard-Barton, D., *Wellsprings of knowledge : building and sustaining the sources of innovation.* Boston, Mass. : Harvard Business School Press, 1995.

[88] Li, N., Chen, L., and Low, S., "Optimal demand response based on utility maximization in power networks," in *IEEE Power and Energy Society General Meeting*, pp. 1–8, 2011.

[89] Liu, Y. and Chen, M., "A review of nonintrusive load monitoring and its application in commercial building," in *IEEE 4th Annual International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER)*, pp. 623–629, 2014.

[90] Lorenz, E., Hurka, J., Heinemann, D., and Beyer, H., "Irradiance forecasting for the power prediction of grid-connected photovoltaic systems," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 2, no. 1, pp. 2–10, 2009.

[91] Luh, P., Ho, Y., and Muralidharan, R., "Load adaptive pricing: An emerging tool for electric utilities," *IEEE Transactions on Automatic Control*, vol. 27, no. 2, pp. 320–329, 1982.

[92] Maharjan, S., Zhu, Q., Zhang, Y., Gjessing, S., and Basar, T., "Dependable demand response management in the smart grid: A stackelberg game approach," *IEEE Transactions on Smart Grid*, vol. 4, no. 1, pp. 120–132, 2013.

[93] Maier, M. W. and Rechtin, E., *The art of systems architecting.* CRC Press, 2009.

[94] Maier, M. W., "Architecting principles for systems-of-systems.," *Systems Engineering*, vol. 1, no. 4, pp. 267–284, 1998.

[95] Mason, R. and Mitroff, I., *Challenging strategic planning assumptions: Theory, cases, and techniques.* Wiley-Interscience, 1981.

[96] McDaniel, P. and McLaughlin, S., "Security and privacy challenges in the smart grid," *IEEE Security Privacy*, vol. 7, no. 3, pp. 75–77, 2009.

[97] McKinsey, "McKinsey on smart grid," 2010.

[98] McNaughton, G. and Saint, R., "Enterprise integration implications for home-area network technologies," in *Innovative Smart Grid Technologies (ISGT)*, pp. 1–5, 2010.

[99] Meng, F.-L. and Zeng, X.-J., "An optimal real-time pricing for demand-side management: A stackelberg game and genetic algorithm approach," in *International Joint Conference on Neural Networks (IJCNN)*, pp. 1703–1710, 2014.

[100] Miller, C., "Hybrid management: Boundary organizations, science policy, and environmental governance in the climate regime," *Science, Technology, and Human Values*, no. 4, p. 478, 2001.

[101] MIT, "The future of the electric grid: An interdisciplinary mit study," 2011.

[102] Mo, Y., Kim, T.-H., Brancik, K., Dickinson, D., Lee, H., Perrig, A., and Sinopoli, B., "Physical security of a smart grid infrastructure," *Proceedings of the IEEE*, vol. 100, no. 1, pp. 195–209, 2012.

[103] Mohsenian-Rad, A.-H. and Leon-Garcia, A., "Optimal residential load control with price prediction in real-time electricity pricing environments," *IEEE Transactions on Smart Grid*, vol. 1, no. 2, pp. 120–133, 2010.

[104] Mohsenian-Rad, A.-H., Wong, V., Jatskevich, J., Schober, R., and Leon-Garcia, A., "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *IEEE Transactions on Smart Grid*, vol. 1, no. 3, pp. 320–331, 2010.

[105] Moore, K., "Organizing integrity: American science and the creation of public interest organizations, 1955-1975," *American Journal of Sociology*, no. 6, p. 1592, 1996.

[106] Moslehi, K. and Kumar, R., "A reliability perspective of the smart grid," *IEEE Transactions on Smart Grid*, vol. 1, no. 1, pp. 57 – 64, 2010.

[107] Najmeddine, H., El Khamlichi Drissi, K., Pasquier, C., Faure, C., Kerroum, K., Diop, A., Jouannet, T., and Michou, M., "State of art on load monitoring methods," in *IEEE 2nd International Power and Energy Conference*, pp. 1256–1258, 2008.

[108] Narayanamurti, V., Anadon, L. D., and Sagar, A. D., *Institutions for energy innovation: A transformational challenge*. Harvard University, 2009.

[109] Narayanamurti, V., Anadon, L. D., and Sagar, A. D., "Transforming energy innovation," *Issues in Science and Technology*, vol. 26, no. 1, pp. 57 – 64, 2009.

[110] National Academies Press, "Facilitating interdisciplinary research," 2005.

[111] National Energy Technlogy Laboratory, "A vision for the modern grid," 2007.

[112] National Energy Technlogy Laboratory, "Presentation: Ferc – naruc smart grid collaborative meeting," 2008.

[113] National Energy Technlogy Laboratory, "Environmental impacts of smart grid," 2011.

[114] National Institute of Standards and Technology, "Board of new smart grid panel 'boots up' – key position filled and next steps assigned," 2009.

[115] National Institute of Standards and Technology, "Nist framework and roadmap for smart grid interoperability standards, release 1.0," 2010.

[116] National Institute of Standards and Technology, "Nist smart grid collaboration wiki for smart grid interoperability standards," 2014.

[117] Olson, G. M. and Olson, J. S., "Distance matters," *Human-Computer Interaction*, vol. 15, no. 2/3, pp. 139 – 178, 2000.

[118] Pacific Gas and Electric Company, "Smart meter opt-out proposal," in *proposal filled on Mar. 24, 2011 for CPUC consideration.*

[119] Pochet, Y., W. L. A., *Production planning by mixed integer programming.* Springer, 2006.

[120] Ponemon Institute, "Perceptions about privacy on the smart grid," 2009.

[121] Power Systems Engineering Research Center, "Reliability, electric power, and public vs. private goods: A new look at the role of markets," 2008.

[122] Power Systems Engineering Research Center, "Notes from the general session discussions, future grid initiative workshop, december 7, 2011, at university of california, berkeley, ca," 2011.

[123] Qian, L. P., Zhang, Y., Huang, J., and Wu, Y., "Demand response management via real-time electricity price control in smart grids," *IEEE Journal on Selected Areas in Communications*, vol. 31, no. 7, pp. 1268–1280, 2013.

[124] Rittel, H. W. J. and Webber, M. M., "Dilemmas in a general theory of planning," *Policy Sciences*, vol. 4, no. 2, pp. 155 – 169, 1973.

[125] Ritzer, G. and Jurgenson, N., "Production, consumption, prosumption: The nature of capitalism in the age of the digital 'prosumer'," *Journal of Consumer Culture*, vol. 10, no. 1, pp. 13 – 36, 2010.

[126] Robinson, J., *Economic philosophy.* Aldine Pub. Co., 1962.

[127] Roozbehani, M., Materassi, D., Ohannessian, M., and Dahleh, M., "Robust and optimal consumption policies for deadline-constrained deferrable loads," *IEEE Transactions on Smart Grid*, vol. 5, pp. 1823–1834, July 2014.

[128] Saber, A. and Venayagamoorthy, G., "Efficient utilization of renewable energy sources by gridable vehicles in cyber-physical energy systems," *IEEE Systems Journal*, vol. 4, no. 3, pp. 285–294, 2010.

[129] Saint Marc (de), H., *Les champs de braises. Mémoires.* Perrin, 1981.

[130] Samadi, P., Mohsenian-Rad, A.-H., Schober, R., Wong, V., and Jatskevich, J., "Optimal real-time pricing algorithm based on utility maximization for smart grid," in *First IEEE International Conference on Smart Grid Communications (SmartGridComm)*, pp. 415–420, 2010.

[131] Samadi, P., Mohsenian-Rad, H., Wong, V., and Schober, R., "Real-time pricing for demand response based on stochastic approximation," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 789–798, 2014.

[132] Sapsed, J. and Salter, A., "Postcards from the edge: Local communities, global programs and boundary objects," *Organization Studies*, vol. 25, no. 9, pp. 1515 – 1534, 2004.

[133] Schrijver, A., *Theory of linear and integer programming*. Wiley, 1986.

[134] Selten, R., "What is bounded rationality?," in *Bounded rationality: The adaptive toolbox* (Gigerenzer, G. and Selte, R., eds.), Cambridge, MA: The MIT Press, 2001.

[135] Sharachchandra, L. and Norgaard, R. B., "Practicing interdisciplinarity," *BioScience*, no. 11, pp. 967–975, 2005.

[136] Simon, H. A., *Models of man; social and rational*. Oxford England: Wiley, 1957.

[137] Simon, H. A., "From substantive to procedural rationality," in *Method and appraisal in economics* (Latsis, S. J., ed.), Cambridge University Press, 1976.

[138] Simon, H., "The structure of ill structured problems," *Artificial Intelligence*, vol. 4, no. 3, pp. 181 – 201, 1973.

[139] Star, S. L., "This is not a boundary object: Reflections on the origin of a concept," *Science, Technology, and Human Values*, no. 5, pp. 601–617, 2010.

[140] Star, S. L. and Griesemer, J. R., "Institutional ecology, 'translations' and boundary objects: Amateurs and professionals in berkeley's museum of vertebrate zoology, 1907-39," *Social Studies of Science*, no. 3, p. 387, 1989.

[141] Strauch, R. E., "'squishy' problems and quantitative methods," *Policy Sciences*, vol. 6, no. 2, pp. 175 – 184, 1975.

[142] Swan, J., Bresnen, M., Newell, S., and Robertson, M., "The object of knowledge: The role of objects in biomedical innovation," *Human Relations*, vol. 60, no. 12, pp. 1809 – 1837, 2007.

[143] Tapscott, D., *The digital economy : Promise and peril in the age of networked intelligence*. New York: McGraw-Hill, 1996.

[144] Tapscott, D. and Williams, A. D., *Wikinomics: How mass collaboration changes everything*. New York: Portfolio, 2006.

[145] Tapscott, D. and Williams, A. D., *MacroWikinomics: Rebooting business and the world.* New York: Portfolio Penguin, 2010.

[146] The GridWise Architecture Council, "GridWise interoperability context-setting framework," 2008.

[147] Toffler, A., *The third wave.* New York : Morrow, 1980.

[148] Tomi, J. and Kempton, W., "Using fleets of electric-drive vehicles for grid support," *Journal of Power Sources*, vol. 168, pp. 459 – 468, 2007.

[149] Triki, C. and Violi, A., "Dynamic pricing of electricity in retail markets," *Quarterly Journal of Operations Research*, vol. 7, no. 1, pp. 21–36, 2009.

[150] Ulrich, W., "Beyond methodology choice: Critical systems thinking as critically systemic discourse," *The Journal of the Operational Research Society*, no. 4, p. 325, 2003.

[151] US Congress, "HR Bill 5696–Electric Consumer Right to Know Act," 2010.

[152] U.S. Department of Energy, "Smart grid system report," 2009.

[153] U.S. Department of Energy, "Smart grid system report," 2012.

[154] U.S. Energy Information Administration, "Updated capital cost estimates for electricity generation plants," 2010.

[155] U.S. Energy Information Administration, "Annual energy outlook 2013," 2013.

[156] Varillon, F., *Joie de croire, joie de vivre.* Le Centurion, 1981.

[157] Wallis, J. and Dollery, B., *Market failure, government failure, leadership and public policy.* New York: St. Martin's Press, 1999.

[158] Walton, J. and Gohn, B., "Smart appliances research report."

[159] Wei, M., Patadia, S., and Kammen, D. M., "Putting renewables and energy efficiency to work: How many jobs can the clean energy industry generate in the us?," *Energy Policy*, vol. 38, pp. 919 – 931, 2010.

[160] Weimer, D. and Vining, A. R., *Policy analysis: Concepts and practice.* Pearson, 2010.

[161] Weiss, C. and Bonvillian, W., *Structuring an energy technology revolution.* Cambridge, MA : MIT Press, 2009.

[162] Wenger, E., *Communities of practice.* Cambridge University Press, 1998.

[163] WERBOS, P., "Computational intelligence for the smart grid – history, challenges, and opportunities," *IEEE Computational Intelligence Magazine*, vol. 6, no. 3, pp. 14 – 21, 2011.

[164] WHITE, D. D., CORLEY, E. A., and WHITE, M. S., "Water managers' perceptions of the science-policy interface in phoenix, arizona: Implications for an emerging boundary organization," *Society and Natural Resources*, vol. 21, no. 3, pp. 230 – 243, 2008.

[165] WOLF, C., *Markets or governments: Choosing between imperfect alternatives.* RAND Corporation, 1988.

[166] XIA, L., MONROE, K. B., and COX, J. L., "The price is unfair! a conceptual framework of price fairness perceptions," *Journal of Marketing*, vol. 68, no. 4, pp. 1 – 15, 2004.

[167] YAKURA, E. K., "Charting time: Timelines as temporal boundary objects," *Academy of Management Journal*, vol. 45, no. 5, pp. 956 – 970, 2002.

[168] YANG, P., TANG, G., and NEHORAI, A., "A game-theoretic approach for optimal time-of-use electricity pricing," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 884–892, 2013.

[169] YI, P., DONG, X., IWAYEMI, A., ZHOU, C., and LI, S., "Real-time opportunistic scheduling for residential demand response," *IEEE Transactions on Smart Grid*, vol. 4, no. 1, pp. 227–234, 2013.

[170] YU, Z., MCLAUGHLIN, L., JIA, L., MURPHY-HOYE, M., PRATT, A., and TONG, L., "Modeling and stochastic control for home energy management," in *IEEE Power and Energy Society General Meeting*, pp. 1–9, 2012.

[171] ZEIFMAN, M. and ROTH, K., "Nonintrusive appliance load monitoring: Review and outlook," *IEEE Transactions on Consumer Electronics*, vol. 57, no. 1, pp. 76–84, 2011.

[172] ZHANG, J. and LIU, Z., "Calculating some inverse linear programming problems," *Journal of Computational and Applied Mathematics*, vol. 72, no. 2, pp. 261–273, 1996.

[173] ZHANG, J. and LIU, Z., "A further study on inverse linear programming problems," *Journal of Computational and Applied Mathematics*, vol. 106, no. 2, pp. 345–359, 1999.

[174] ZHAO, Z., LEE, W. C., SHIN, Y., and SONG, K.-B., "An optimal power scheduling method for demand response in home energy management system," *IEEE Transactions on Smart Grid*, vol. 4, no. 3, pp. 1391–1400, 2013.

[175] Zhu, Z., Tang, J., Lambotharan, S., Chin, W. H., and Fan, Z., "An integer linear programming based optimization for home demand-side management in smart grid," in *IEEE PES Innovative Smart Grid Technologies (ISGT)*, pp. 1–5, 2012.

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